



Final Report

**EXTREMIST IDEOLOGICAL INFLUENCES ON TERRORIST DECISION
FRAMEWORKS**

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Prepared for:

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Prepared by:

Winston R. Sieck, Ph.D.
Global Cognition, LLC
1771 Southview Dr.
Yellow Springs, OH 45387
www.globalcognition.org

Antonio Penta, Ph.D.
Paul Smart, Ph.D.
School of Electronics and Computer Science
University of Southampton
Southampton, UK SO17 1BJ
www.ecs.soton.ac.uk

LTC (ret.) David Rababy
Rababy & Associates, LLC
10400 Courthouse Rd. Suite 290
Spotsylvania, VA 22407
www.rababyassociates.com

Jennifer L. Smith
Jessica L. Marcon, Ph.D.
Cognitive Solutions Division
Applied Research Associates, Inc.
1750 Commerce Center Blvd. North
Fairborn, OH 45324-6333
www.ara.com/CognitiveSolutions

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14. ABSTRACT Two cultural studies were conducted to clarify the ideological characteristics that serve as enablers for extreme action. The approach for both studies was to collect and analyze knowledge source materials from the World Wide Web. The World Wide Web is a rich source of cultural information that provides important clues as to the beliefs, attitudes and values of group members. Documents and postings from extremist and moderate sources were collected and translated. Relevant passages were then extracted and analyzed in order to elucidate the ideological characteristics within them. Human cultural researchers conducted the analysis in Study 1 and a new model of core extremist beliefs-values was constructed. In Study 2, the model was further tested by using computational text analysis methods to aid in analyzing sentiment from the web-based sources. Such methods remain at a early research phase of development, so new approaches and techniques were developed. Study 2 served both to corroborate the model of extremist beliefs-values devised in Study 1, as well as to advance the state of the art in automated sentiment analysis. The computational method for measuring cultural values in web-based resources adds another significant component to the cultural analysts' toolkit.					
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EXECUTIVE SUMMARY

The overall goal of this project was to understand extremist ideological influences underlying terrorist and insurgent behavior, in a way that supports the future development of predictive models of adversary decision making. The *National Military Strategic Plan for the War on Terrorism* identifies extremist ideology as the enemy's strategic center of gravity, and the Department of Defense (DOD) plays a significant role in establishing an environment unfavorable to extremist ideas, recruiting, and support (Wald, 2006). Yet, the specific ideological characteristics that serve as enablers for extreme action have not been well understood. Two cultural studies were conducted to clarify these ideological characteristics.

The overall study approach was to collect knowledge source materials from the World Wide Web. The World Wide Web is a rich source of cultural information. Aside from resources that provide background information about cultural groups (e.g., their history, geographical location and ethno-linguistic properties), the Web also provides important clues as to the beliefs, attitudes and values of group members. Once the knowledge sources were collected and translated, relevant passages were then extracted and analyzed in order to elucidate the ideological characteristics within them. In Study 1, human cultural researchers conducted the analysis, and a new model of beliefs-values related to extremist thought was constructed. In Study 2, the model was further tested by using computational text analysis methods to aid in analyzing sentiment from the web-based sources. Such methods remain at an early research phase of development, so new approaches and techniques were developed for accomplishing automated sentiment analysis. Study 2 served both to corroborate the model of extremist beliefs-values devised in Study 1, as well as to advance the state of the art in automated sentiment analysis.

The current advances in automated sentiment analysis have been essential for applications to cultural modeling. Recent research in cultural modeling techniques has emphasized new ways of representing cultural knowledge (Sieck, Rasmussen, & Smart, 2010a). These representation formats have further led to novel developments in areas of semi-structured and structured elicitation methods for direct human data collection (Sieck, Rasmussen, Smith, & Kakar, 2010c), as well as in simulating influences of information on culturally-shared beliefs (Sieck, Simpkins, & Rasmussen, 2011). A computational method for measuring cultural values in web-based resources adds another significant component to the cultural analysts' toolkit. By providing a means to extract and quantify the cultural values embedded in large and increasing volumes of text being generated on the web, the present work moves a step closer to the realization of a "social radar" for monitoring and modeling changes in the sentiments of citizens and leaders (Maybury, 2010).

INTRODUCTION

Advances in understanding the reasons behind terrorism have been made in the last several years; though the evidential research base remains thin (Atran & Sageman, 2006). Before discussing potential causes of terrorism, however, it is useful to offer a definition. The DOD defines terrorism as:

The calculated use of violence or threat of violence to attain goals, political, religious, or ideological in nature. This is done through intimidation, coercion, or instilling fear. Terrorism involves a criminal act that is often symbolic in nature and intended to influence an audience beyond the immediate victim (Department of the Army, 1983).

Generally, terrorist support and recruitment is not due to any single causal factor, but instead stems from the interplay between political aspirations of terrorist groups, vulnerable individuals, employment of terrorist ideology, and wider social support for terrorism. These latter components increasingly depend on religious doctrine being used to support the underlying ideology (Speckhard, 2006). A general characterization of the overall strategy of terrorist organizations is to:

- motivate ordinary persons to carry out terrorist acts to meet their objectives
- exploit moral outrage and feelings of humiliation based on political events
- convince by means of texts used in behalf of terror ideology

We discuss each of these components of terrorist strategy in turn. First, with respect to profiles of individuals, what research there is indicates that suicide terrorists have no appreciable psychopathology and are at least as educated and economically well off as their surrounding populations (Atran, 2003). Furthermore, education does not appear to be correlated with support for terrorism. Finally, although economic despair may provide a partial answer, it does not offer a complete explanation (Barsalou, 2002). Importantly, individuals who are vulnerable to terrorist recruitment are not motivated to take part in suicide terrorism without some form of ideology to guide them, as well as an overall organization to support their activities (Speckhard, 2006). In the case of Islamic terrorism, the focus of the current report, the terrorist ideology is well integrated with a larger body of religious doctrine.

The balance of evidence suggests that a primary factor for recruitment of Islamic terrorists (“Jihadists”) is that they come from at least moderately religious backgrounds. For example, interviews with terrorist recruits in Pakistan indicated that, “None were uneducated, desperately poor, simple minded or depressed,” and “all were deeply religious.” They believed that their acts were “sanctioned by the divinely revealed religion of Islam” (Hassan, 2001). Furthermore, it also seems clear that religiosity is fostered as a part of the indoctrination process and those external events can trigger greater attention to religion. For example, Bosnian Muslims typically report not considering religious affiliation a significant part of identity until seemingly arbitrary violence forced awareness upon them (Atran, 2003). Keep in mind, however, that the root of terrorist motive is political dissent, and that religion is used as a vehicle for achieving political ends. The question we address is how, specifically, is religious doctrine used to advance terrorist agendas? Our thesis is that influences of religious messages can be understood to operate at two

psychological levels, the cognitive level and the metacognitive level.¹ Furthermore, these two levels correspond to the second and third components of the terrorist strategy.

Cognitive Level

The second component of Jihadist strategy is to exploit public emotional responses to political events. Terrorist organizations appear to be quite sophisticated in their use of modern media, including use of the World Wide Web to disseminate vivid imagery of moral wrongdoing by Americans and other agents of the West. Furthermore, humiliating and morally outrageous events are not considered isolated or random, but rather are interpreted within an overarching framework that a unified Western strategy exists to promote a “war against Islam” (Sageman, 2008).

This second strategy relies heavily on terrorist communication of specific aspects from their ideological framework to shape the common perspective of their intended audiences. For the approach to be successful, the ideas they are promoting must fit within the cultural meaning systems shared across the population they are addressing. Hence, this second strategy operates at the “cognitive” level. One application of cultural modelling to terrorism research is to explicitly map out the relevant cultural meaning systems in order to better understand how and why various messages appear to be effective in influencing people’s attitudes and garnering their support (see Appendix A; Sieck, 2011). Before addressing cultural cognition in terrorism, however, we first need to define culture from a cognitive perspective.

There is a somewhat natural tendency to talk about culture as if it were a concrete, material thing. It is sometimes described as something people belong to, or as an external substance or force that surrounds its members and guides their behavior. Although it is sometimes difficult to avoid speaking in these metaphorical terms, such an ethereal view does not provide a useful basis for a technical definition. An alternative approach begins by defining culture in terms of the widely shared ideas (such as concepts, values, and beliefs) that comprise a shared symbolic meaning system (Rohner, 1984). Within this conception, a population, or identifiable segments of a population, maintains approximately equivalent and complementary learned meanings. In this statement, ‘approximately equivalent’ acknowledges that no two people within a culture share exactly the same ideas, but rather highly similar meanings are shared by most members of a society. The ‘complementary’ component refers to the fact that sharing of specialized knowledge depends on status and roles within a society (e.g., an imam and farmer).

Taking this conception a step further, it is currently popular within cognitive science to draw on a disease metaphor for understanding cultural ideas, describing the ideas that spread widely through a population and persist for substantial periods of time as especially ‘contagious’ (Sperber, 1996). This theoretical framework is often referred to as the epidemiological view of culture, drawing on the general sense of epidemiology as describing and explaining the distributions of any property within a population. The starting point for working from this epidemiological view is the individual idea as an atomic unit. People typically use the word *idea*

¹ Each of these levels can be seen to interact with emotional systems, as well. However, our position is that religious messages do not directly influence emotions, but rather that cognitive interpretations of messages evoke emotions, sometimes if not often, very quickly and intensely.

to refer to any content of the mind, including conceptions of how things are and of how things should be. For instance, individuals may hold the concept that Western nations are joined together in a covert war against Islam. Their minds may also contain the value that imported Western ideals, such as the separation of religious and state affairs, are generally bad and so should be avoided. The Cultural Network Analysis (CNA) approach to cognitive-cultural modelling is that cultural knowledge consists of shared networks of ideas, and that there is value in explicitly considering clusters of ideas and their interrelationships (Sieck, Rasmussen, & Smart, 2010b). Networks of causally-interconnected ideas are often referred to as folk theories or *mental models* (Gentner & Stevens, 1983). Such networks constitute people's explanations for how things work, and result in judgments and decisions that influence their behaviour.

From this perspective, *culture* refers to mental models, and other contents of the mind, for which there is some level of concordance across members of a population over a period of time. A potential issue associated with this definition of culture is how, then, to define the population of interest. The term *cultural group* refers to a population or sub-population of people that largely share the interconnected ideas of interest. The issue is that cultural groups are distinct from, but related to, demographic groups (i.e., groups based on nationality, educational status, etc.) in that the demographic delineations relevant to a particular cultural group will depend on how widespread the cultural ideas of interest are. For example, Sunni and Shia sectarian distinctions make little difference if the idea of interest is, "There is no god but Allah, and Mohammad is his prophet." However, if the relevant common beliefs include those pertaining to the 13th Imam, then that demographic does become important. Hence, the relevant cultural group for a study will depend on the *cultural domain*, that is, the kind and topic of knowledge of interest.

Consider a Sunni Muslim extremist conception of socio-political relationships between Islam and the West. A mental model of such relationships contains an individual person's concepts as well as their understanding of the causal relationships between concepts, i.e., the antecedents and consequences of political activities and their outcomes. This mental model influences the individual's expectations for how socio-political relationships will unfold and provides a framework for selecting behaviors and goals within this context. Figure 1 provides a network representation that might describe a Sunni Muslim's mental model of current political events. The set of ideas represented in Figure 1 were extracted from articles that describe jihadist narratives (Hafez, 2007; Sageman, 2008). Figure 1 depicts a number of ideas using circles, lines, and color: circles represent concepts, lines represent causal beliefs, and color represents value, with "green" viewed positively, and "red" viewed negatively. These ideas include simple concepts such as "Western arrogance" and "Muslim honor" represented as circles. It also includes causal ideas, such as the development of a new Islamic caliphate would decrease the extent of Western dominance and bring about a return of past Islamic glory. Lines in the figure represent these causal ideas, with +/- indicating the direction of the causal belief. Finally, Figure 1 portrays ideas of desired states or value using color, as well as a logical flow across desired states. Developing an Islamic caliphate is a good thing. Maintaining (and enhancing) Muslim honor is likewise valued.

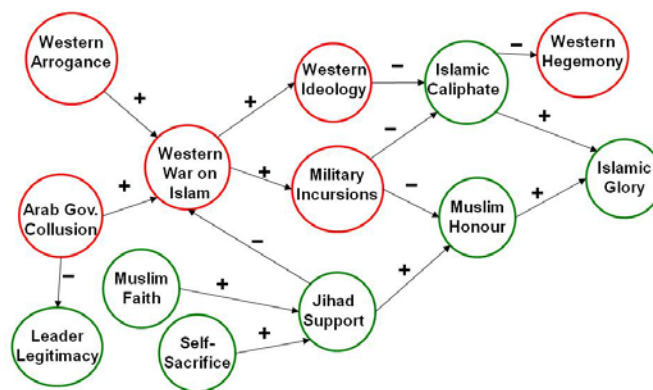


Figure 1. Sunni Jihadist Cultural Model of political relationships.

Holding the beliefs described by this mental model is likely to have fairly strong consequences for how a person will decide and act in a number of specific, relevant situations. For example, according to the model, jihad is viewed positively and should be supported by the model's adherents due to the perceived anticipated consequences for Muslims. Most directly, support for jihad decreases the chances that the West will continue its war against Islam, and enhances collective Muslim honor.

As implied by the name, mental models reside inside the heads of individuals. However, when people communicate with each other in any variety of modes, they develop mental models that may begin to resemble one another. Mental models can spread widely throughout a population, becoming 'cultural' in the sense of being shared by many of its members. A *cultural model* refers to an external representation of a set of culturally-shared mental models that is constructed by a researcher (Sieck et al., 2010b). A cultural model represents a consensus of the mental models for a particular cultural group and domain. Hence, for the Sunni Muslims who hold beliefs similar to the elements in this model, Figure 1 serves as one of their *cultural models* in the domain of socio-political relationships.

Resulting cultural models and descriptions of their dynamics from such studies can provide considerable insight into the thinking behind communications that stem from terrorist groups. They also provide a basis for developing effective counter-communications by aiding in the determination of what makes for culturally meaningful messages (Sieck, 2010). Cultural models would allow for making predictions concerning the effectiveness of a message by providing the opportunity to assess potential unintended inferences that individuals with a certain knowledge structure might make. Specifically, in a cultural models diagram, each concept and causal belief represents an opportunity to effect a change in beliefs or concepts. Hence, such diagrams can provide an orderly basis for determining the content of communications. Messages are created so as to affect the values of the most vulnerable concept nodes (i.e., those for which there is the least consensus) which then propagate across perceived influences to affect the values of other concepts. These effects spread through the cultural belief network, ultimately changing the value in overall perceptions or cognitions (Sieck et al., 2011). With this CNA approach, information efforts focus on transmitting the most relevant information to effect conceptual change in a way that makes sense within the cultural group's understanding. However, one aspect that CNA does not take into account is the *certainty* with which individual members of a culture hold their beliefs. Certainty plays a central role as the third component of the terrorist strategy.

Metacognitive Level

The third component of terrorist strategy is to ensure that recruits are convinced so thoroughly that they will not consider backing out, let alone feel any mercy or remorse about their actions. For a suicide terrorist in particular, this means they will carry forward with no doubt about their decision to die in order to kill others (Speckhard, 2006). Researchers have sometimes described the fully indoctrinated terrorist as a “Cosmic Warrior,” who harbors no ambiguity or doubt about the mission or means to accomplish it (Juergensmeyer, 2000). This religious conviction includes a fundamental belief that the terrorist knows the mind of God. Such a belief justifies a complete lack of tolerance for divergent ideas, even of other believers who disagree with the terrorist group on specific issues.

From a model-development standpoint, we conceive of the decision to accept the terrorist group’s worldview as the central node within the highest-level of a hierarchy of terrorist decision frameworks. Developing this meta-level framework of absolute conviction in support of the full hierarchy of terrorist decision frameworks is understood to rest on a subtle and slow indoctrination process. Although we know that the successful exploitation of religious texts is a key component of the process, the set of specific religious ideas that promote such certitude remains unclear. That is, we know that terrorists become totally convinced through religious texts (Speckhard, 2006). But, what in the religious doctrine accomplishes such moral conviction? How do specific religious ideas eliminate doubt?

We propose that, as new recruits become indoctrinated with beliefs justifying terrorism, they are also being indoctrinated with specific “metacognitive” beliefs drawn from Islamic sources that serve to erase doubt in the terrorist agenda and provide psychological defenses against contrary views. In general, metacognition refers to knowledge and beliefs about one’s own knowledge and thought processes (Flavell, 1979; Metcalfe & Shimamura, 1994). Whereas the cognitive level addresses *what* to believe about the world, the metacognitive level addresses instead *how* one should believe. We refer to the metacognitive beliefs introduced by extremists and terrorists as “Polarizing Metacognitive Ideas” (PMIs). For example, the idea that pluralism results in spiritual contamination is a PMI because holding it serves to discount any “cognitive level” ideas that diverge from one’s current belief set. Another example is that innovative ideas are necessarily false and evil. PMIs are specific kinds of beliefs that affect the cognitive processes that govern feelings of confidence in worldviews. The excessive levels of confidence that ultimately result from collections of PMIs serve to sanction extreme actions (e.g., supporting or attempting to accomplish nuclear terrorism). Past research has shed considerable light on the cognitive processing underlying overconfidence and its relationship to decisiveness both within and across cultures (Sieck, Merkle, & Van Zandt, 2007; Yates et al., 2010). The past work on overconfidence provides important grounding for determining the polarizing or moderating effects of specific metacognitive ideas. In the current study, we use this past work in conjunction with new analyses of the contents of Islamic web-based discussions and sources in order to test our primary hypothesis that moderate and extremist Islamic ideologies can be discriminated by embedded metacognitive beliefs relevant to certainty. Specifically, we expect that extremist Islamic sources will include metacognitive ideas that foster cognitive processing that leads to increased confidence in beliefs; whereas, moderate Islamic sources will tend to include metacognitive ideas that lead to more balanced confidence in one’s beliefs.

USING THE WORLD WIDE WEB TO MEASURE CULTURAL VALUES: OVERVIEW OF STUDIES AND METHODS

The World Wide Web is a rich source of cultural information. Aside from resources that provide background information about cultural groups (e.g., their history, geographical location and ethno-linguistic properties), the Web also provides important clues as to the beliefs, attitudes and values of group members. It is also readily available and free, making it very accessible. The use of the Web as a cultural knowledge source is, however, complicated by its large-scale nature (which makes relevant information hard to find) and the fact that relevant information is often represented in natural language formats (this limits the kind of automated processing that can be undertaken). Ideally, what is required is a method for extracting culture-relevant information from Web-based resources and representing this information in a way that supports cultural modeling and analysis.

Web-based Collection

The overall study approach was to collect knowledge source materials from the World Wide Web, translating from Arabic to English where needed. We then extracted relevant passages for classification and comparison purposes in order to elucidate the role of metacognitive ideas and other ideological characteristics within them. Our initial search criteria focused on materials that provided Islamic justifications for Jihad and/or terrorism from leaders and learned clerics (on the extremist side), or documents that provided Islamic-based counter-arguments to Jihad/terrorism (or arguments that constrain it) on the moderate side. These criteria also provided our operational definitions of extremist and moderate web sources, respectively. We collected 58 documents (2,011 pages) using these initial search parameters. Findings from the initial round of collection and other sources suggested a set of search parameters that focused more on metacognitive ideas, including a new set of questions, phrases, and terms for use in searching Arabic web documents. We collected another 210 documents (1,723 pages) using these refined search parameters. The specific search parameters guiding the second round of collection along these dimensions included:

1. What is the Islamic concept of knowledge? What is the Islamic attitude towards learning? What is the feeling about change in thinking or culture? Arabic word: bida
2. What is the Islamic feeling about different ways of knowing? Is there a contradiction between Islamic religion and science? What is the Islamic stance on pluralism? Arabic words: kafir, taq'yya
3. What should be the relationship between Muslims and non-Muslims? Should Muslims interact with non-Muslims? How much, under what conditions? How to treat non-Muslims?
4. How much freedom of thought is there in Islam? Can believers interpret Koran/other texts? Should believers rely on authority to understand Koran in Islam? What about critical thinking, independent reflection in Islam? Arabic words: ijtihaad, at-taffakkur, at-taddabbur
5. How zealous or strict should Muslims be in their spiritual practices? What does Islam say about moderation, avoiding excesses? Arabic word: at-tassut

We collected documents from three different collections of sources on the web. First, we conducted searches of websites associates with various known Islamic extremists, which we describe in more detail below. In order to establish moderate baselines for comparison, we conducted parallel collection from broad-based Google searches of two additional sources: U. S. English Islamic sites and pan-Arabic language Islamic sites.

With respect to the extremist websites, we searched a variety of sources, including religious teachers who post sermons (e.g., Sheikh Mohammed Alvzazi; Sheikh Abu Saad Al-Ameli, and Mufti Sheikh Mohammed Saleh), discussion forums such as Altartosi, Al Fazzazi, Tawhed, and terrorist organizations websites such as AQ, Hezbollah, Hamas, Al-Quds. We provide examples of some of the most productive sites for illustration:

<http://www.scholarofthehouse.org/>

A website dedicated to Khaled Abou el-Fadl, which has his books and lectures available for download.

<http://muslimdefenseforce.islamicink.com/lectures-of-sheikh-faisal/>

This website does not function reliably, but when it is functioning, it contains an abundance of extremist content, including lectures by Sheikh Faisal, Awlaki and other “leaders of jihad.” The website has numerous relevant sections, such as sections dedicated to Taliban military operations, pictures of “American Zionist crusader hell in Afghanistan,” ummah news, and the mujahedeen in pictures.

<http://www.revolutionmuslim.com/2010/07/islamic-ruling-on-permissibility-of.html>

This is a very popular website which contains links to videos and articles supporting the extremist scholars, such as Shaykh Omar Bakri Muhammad, Abu Hamza al-Masri, Abdullah Azzam, and Anjem Choudary. While the website is very well known and contains links in which participants who post comments openly support jihad, the creator of the website makes a point to never actually incite jihad or say anything that would be considered “extremist” in nature. The creator insists the website is to serve as an up-to-date news source for Muslims that will counter the mainstream propaganda put forth by other news agencies.

<http://www.abubaseer.bizland.com/>

This is Abu Basir al Tartusi’s website, in Arabic. The site has a publications page as well as a research and articles page where documents are made available to read and/or download. The site also has lectures available in an audio format. On the website, Al Tartusi states numerous reasons why the website was created, including to serve as “an invitation to jihad in the cause of Allah which is the Ummah’s only way to change this state of humiliation and to establish a rightly-guided Islamic way of life.”

<http://iskandrani.wordpress.com/>

This website has a scholars section which includes 240 lectures and postings regarding 30 scholars, including Abdullah Azzam, Abu Basir, Abu Muhammad al-Maqdisi, Abu Qatadah,

al-Khatib al-Baghdadi and many others. The website has not been updated since October 2009, but still serves as a good source of information. It also contains a books and PDFs section with downloadable materials from the above-mentioned scholars.

<http://izzatulillah.wordpress.com/>

This website has books available from different scholars including Maqdisi. Additionally, material can be found in the daily/weekly web postings.

<http://www.tawhed.net/> and <http://www.tawhed.ws/>

This website is a very good resource for information, including a section with books from scholars that are available for download. Some examples include Azzam and Qutb, and a link to “39 Ways to Serve and Participate in Jihad.” This website includes articles about and interviews of individuals such as bin Laden, al-Yazid and Adam Gadahn, and an assortment of magazines, such as “The Call of Islam.” There are also links to other similar websites and a library section strictly dedicated to Maqdisi.

<http://www.khayma.com/>

This website has a lot of information and numerous links to explore. The Islam/Islamic Jihad section includes many articles and statements, and includes links to sites for individual extremist groups. There is also a “Lectures” section on the “Islam” link. The website also contains non-extremist information in addition to the Islamic Jihad content.

Translation

The approach for performing analysis on resources, which appeared in Arabic was to have the document translated into English before analyzing it. Transliteration tools and human translation were used in conjunction to perform this task. Transliteration provides a word-for-word translation and often requires a human analyst in the process to make sense of the translated materials. These tools were used in the collection and initial vetting of documents. Human translation was performed on selected documents and segments that best met the study criteria to improve comprehension. In some cases, interviews were conducted with native speakers about specific passages to better understand the context, subtle connotations, and other Islamic references regarding the ideas contained within them.

STUDY 1: EXPLORATORY CULTURAL ANALYSIS

Method

As indicated above, the collection effort was quite extensive, as it was intended to supply information to be used in the automated text analysis study that was the primary focus of Study 2, as well as for the initial “human” analysis effort reported here. In order to maintain a manageable amount of information for human analysis, we randomly selected a subset of documents to work with for extensive qualitative and quantitative analysis purposes. In the end, we settled on 11 documents from Arabic extremist websites and 15 documents from U.S. English mainstream searches. Individual documents varied in length, the complete set included was extensive by qualitative research standards. Two members of the research team then read the 26 documents, and conducted thematic content analyses in order to identify examples of different kinds of metacognitive ideas. Based on the results, the researchers developed a model representing the distinct kinds of metacognitive ideas. The qualitative results section, below contains the model, which is supported by different examples. The researchers then reviewed the documents again, and extracted all the excerpts they identified that appeared to be related to metacognition in some way, or to have implications for metacognitive processing. This process resulted in a set of 521 excerpts for further analysis, as described in the quantitative analysis results section below.

Results

Qualitative Analysis and Results. The initial, thematic analysis results were organized in model of five dimensions of metacognitive ideas. These five dimensions were hypothesized to discriminate between extremist and moderate Islamic ideologies in psychological terms. We discuss each of the dimensions, in turn, including how each relates to increasing confidence in belief at the “cognitive level.” To elucidate each dimension further, we also provide specific examples of Islamic ideological content drawn from the thematic analysis.

1. **Knowledge: Maintenance vs. change at individual or cultural levels.** Cultural ideas that emphasize the priority and continuance of long-established conceptions of the world and associated practices appear to be quite central kinds of polarizing metacognitive ideas, serving as such to increase the level of certainty that existing culturally-shared knowledge and worldviews are correct. On the other hand, beliefs that emphasize knowledge acquisition and change at the individual and cultural levels imply that existing beliefs may be wrong, incomplete, or no longer fit with current situations. Interestingly, such beliefs are sharply contrasted among different groups of Muslims, as illustrated in the following example passages.

Knowledge Maintenance

America...came to change the fundamentals of the nation, changing the curriculum, and the removal of goodness springs in the conscience of the Islamic nation, and blocks the road to awakening

...In ittibaa' (following of) the prophet (saw), which is built upon following his sunnah and turning away from bida' (religious innovations). Sunnah is good and is to be followed, whilst bida' is evil and is to be shunned.

The prophet (saw) has informed us of this in the hadeeth of Hudaifah (ra) in which he said: "The people used to ask the Messenger of Allah (saw) about the good, and I used to ask him about the evil out of fear that it would reach me. ...I further enquired: "Then is there any evil after this good?" He said: "Yes! Callers at the gates of Hell - whoever responds to their call, they will be thrown into the fire." ...Meaning: Whoever obeys the callers of innovation and misguidance then his end will be the fire, because the Prophet (saw) has said: "Every innovation is misguidance and every misguidance is in the fire."

So the innovation is in the fire along with its companion. Whoever obeys the callers of innovation will be led to the Fire and whosoever obeys the callers of Sunnah will be led to Paradise.

We have to acquire knowledge of the Qur'an and the Sunnah upon the understanding of the Salafus-Saalih (Pious predecessors—the first three generations of Muslims) in order to comprehend our state of affairs. However, if we rely on newspapers, magazines and the radio then these media sources belong to the disbelievers, the West. Will they be truthful in their narrations and in their solutions? Do they really want good for the Muslims? Indeed, they do not spread except that which weakens the Muslims and makes them falsely believe in the West.

Knowledge Change

With time God's message takes on a certain form and religious tradition. From time to time scholars add to and amplify this message. Therefore, religion becomes a dynamic and evolving concept, rooted in history but given various interpretations suited to our times and addressing our problems and challenges. We should learn and incorporate what is good in the American experience, listen to new ideas and not be afraid of new interpretation of religious doctrine.

Beside various Qur'anic verses emphasizing the importance of knowledge, there are hundreds of Prophetic traditions that encourage Muslims to acquire all types of knowledge from any corner of the world. Muslims, during their periods of stagnation and decline, confined themselves to theology as the only obligatory knowledge, an attitude which is generally but wrongly attributed to al-Ghazali's destruction of philosophy and sciences in the Muslim world.

'ilm, attainment of which is obligatory upon all Muslims covers the sciences of theology, philosophy, law, ethics, politics and the wisdom imparted to the Ummah by the Prophet (S). Al-Ghazali has unjustifiably differentiated between useful and useless types of knowledge. Islam actually does not consider any type of knowledge as harmful to human beings. However, what has been called in the

Qur'an as useless or rather harmful knowledge, consists of pseudo sciences or the lores prevalent in the Jahiliyyah.

Islam never maintained that only theology was useful and the empirical sciences useless or harmful. This concept was made common by semi-literate clerics or by the time servers among them who wanted to keep common Muslims in the darkness of ignorance and blind faith so that they would not be able to oppose unjust rulers and resist clerics attached to the courts of tyrants. This attitude resulted in the condemnation of not only empirical science but also 'ilm al-kalam and metaphysics, which resulted in the decline of Muslims in politics and economy. Even today large segments of Muslim society, both the common man and many clerics suffer from this malady. This unhealthy and anti-knowledge attitude gave birth to some movements which considered elementary books of theology as sufficient for a Muslim, and discouraged the assimilation or dissemination of empirical knowledge as leading to the weakening of faith.

2. **Coherence: Homogeny vs. diversity (individual and cultural levels).** The recruitment and consideration of a broad set of divergent ideas is typically considered to be critical among the cognitive processes that protect against excessive confidence in ones beliefs (Koriat, Lichtenstein, & Fischhoff, 1980; Lee et al., 1995). Such a thinking style naturally requires that diverse ideas are available, either in individuals' knowledge bases or, perhaps more commonly, distributed among individuals within communities at various levels of granularity. Hence, ideas that stress the acceptability of diversity in beliefs and knowledge ensure the availability of divergent ideas that can enter into decision processes. Ideas that emphasize homogeny in beliefs and knowledge, in contrast, reduce the chances of divergence and hence contribute to increased confidence in decision making. As shown below, specific ideas that emphasize homogeny and diversity were found to correspond with extremist and moderate Muslims, respectively.

Homogeny

The Islamic Jihad has been emptied of its contents through different schemes and weird manners of lying, falsification, and twisting. The knowledgeable ones among the Islamic scholars know quite well that the ultimate goal of Jihad in Islam is for no religion to remain on Earth except Islam, as Allah, the All-Exalted, says, "And fight them until there is no more Fitnah (disbelief and polytheism) and for religion to be that of Allah. But if they cease, then certainly, Allah is All-Seer of what they do." Al-Anfal, verse: 39

People, in the Shari'ah of Allah, are to be classified according to their religion. Among them is the Mu'men (Believer), and the Kafir (infidel); and each is to undergo the terms related to him according to his tenet, his attributes, and they are divided in the way Allah has described them. Allah, the All-Exalted, says, "It is He who created you, but one of you is an unbeliever and another of you is a Believer; and Allah sees what you do." At-Taghabun, verse: 2

Nation of Islam you should know, that the Shiites is the religion that does not meet with Islam, but will also meet with Christians, Jews under the name of the people of the book. It is distortion of the Koran, and insulting the companions, and to challenge the Mothers of the Believers.

Diversity

From time immemorial, man has found different ways of knowing God. Human beings of various intellectual levels have found their own ways to God. Common people have found simple ways; whereas thinkers and philosophers reached the same conclusion on a higher plane of thought.

“The same religion has He established for you as that which He enjoined on Noah, and that which We sent by inspiration to you and that which We enjoined on Abraham, Moses and Jesus: namely that you should remain steadfast in religion, and make no division therein” (Ash-Shura’ 42:13)

Only few messengers were mentioned in the Qur’an; others were alluded to “and messengers we related to you, and messengers we did not relate to you” An-Nesa’a 4:164 & 40:78. Some of these messengers could have been sent to India or China.

3. **Information Exchange: Separation vs. interaction with other groups.** Beliefs concerning religious groups’ interactions with non-members affect confidence by way of the same cognitive mechanisms as beliefs about diversity. That is, these beliefs also enhance or curtail the potential for recruitment of divergent considerations into members’ thought processes. However, in this case, the effects are achieved as a result of beliefs that govern the extent and kind of communication with others who may yield such considerations, rather than by attempting to influence the level of homogeneity/diversity at the source (Snizek & Henry, 1989). Examples of each kind of idea follow:

Maintain Separation from Other Groups

Imam Al-Bukhari - may God have mercy on him - says: “I do not forget the infidels only I know of their destiny.” He said, “Do not pray after a Jew or a Christian, do not eat slaughtered meat from them, do not attend their funerals, and do not take care of their sick.”

Engage in Interaction with Other Groups

Allah (S.W.T) said in surat Al-Mumtahinah, what can be translated as, “Allah does not forbid you (Muslims) to deal justly and kindly with those who have not fought against you in accounts of your religion and who do not drive you out from your homes. Verily, Allah loves those who deal with equity.” (Verse 8). This great verse clearly states the normal and original state for a good relationship between Muslims and Non-Muslims.

The future of Islam depends on safeguarding our convictions and living our Islam and be active members of society, not in hiding or retreating but in reaching out and working with people of other faiths to improve the life of all Muslims and Non-Muslims alike.

4. **Judgment: Authority vs. independence.** Whereas the two prior dimensions emphasized the recruitment of considerations component of cognitive processing, the current dimension is concerned with who is sanctioned (and responsible) to engage in such processing in the first place (Yates, 2003). Beliefs including that only a selected few should make appraisals and judgments pertaining to the religious system can serve to increase confidence in the system across the board in at least a couple of ways. First, many members are often not privy to significant discussions and disagreements that arise from time to time among the group with authority, and hence competing thoughts are unlikely to enter the members' own representations. Secondly, propagation of knowledge for such groups is more likely to emphasize repetition and memorization among adherents. In groups where individuals are assigned more responsibility to interpret situations and exercise judgment themselves, learning tends to include simulations to practice thinking in this manner. Past work on confidence suggests that learning processes that stress memorization lead to increased overconfidence, as compared with more reflective learning. In the Islamic passages examined, two issues emerged that generally seemed to fit within the authority vs. independent judgment dimension. The first was a question of whether or not individuals should choose what religion to belong to (if any), and the second had to do with the extent to which members ought to formulate their own interpretations of religious texts, as well as how various teachings would apply in given situations. A few examples are provided below.

Authority-based Judgment

We do not have in our religion such thing as freedom of belief, but we have in our religion is what the Holy Prophet in Bukhari: "Whoever changes his religion, kill him."

The freedom of belief, as put forward, and personal freedom is not the right one for a Muslim country. Security and stability comes with faith and victory for the religion of Allah, there is no security or stability when it is not security and stability to the religion of God first and foremost

Independence in Judgment

"Say: The truth is from your Lord" Let him who will believe, and let him who will reject faith" (Al-Kahf 18:29)

"Let there be no compulsion in religion: truth stands out clear from error" (Al-Baqara 2:256)

Messengers invite to Allah, but do not force others into belief... "If it had been the will of your Lord, they would all have believed, all who are on earth! Will you then compel mankind to believe against their will!" (Yunus 10:99)

Some Muslims understand that old scholars lived in a different society, and that their opinions are not written in stone. They note that some of these great scholars changed their rulings based on new information and different circumstances. They understand that the Qur'an asks us to think and consider and reach conclusions that help us in our life. They realize that Ijtihad (critical thinking to come up with solutions to new problems) should always be available

5. **Deliberation: Polarized vs. balanced.** The final dimension concerns beliefs about the extent to which a person should consider all evidence and opinions within a situation, weighing the pros and cons of various alternatives during deliberation, or whether they should instead apply (moral) principles in absolute terms. The polarized endpoint of this dimension further emphasizes that one way is absolutely, 100% correct or good, that one's own goals are paramount, so any actions necessary to achieve goals are reasonable, and/or that one should accept opinions that support one's desired beliefs/actions. Examples include:

Polarized Deliberation

One of the most eloquent symptoms of the moral bankruptcy of Western culture is a certain fashionable attitude toward moral issues, best summarized as: "There are no blacks and whites; there are only grays."

Balanced Deliberation

They wish to dig out the rare, strange, and doubtful opinions from here and there in order to strengthen and back up their rants

One needs to know of something called balance and justice...people should look for the truth from themselves and from other than them

A final dimension, initially considered at the qualitative analysis stage, was the frequency and intensity with which believers would be expected to engage in religious rituals and other practices. The idea here is that the more time and energy participants expend on religious practices, to the exclusion of other kinds of activities, then the more salient and highly activated the system of religious knowledge will be to them. Highly activated knowledge tends to be retrieved very fluently, and ease of retrieval has been shown to have a positive influence on confidence (Sanna, Schwarz, & Small, 2002). In the end, we excluded this dimension from further consideration as we did not find direct passages that discuss the intensity of religious practices among adherents. However, expressions regarding strong devotion have been summarized by other researchers (Hafez, 2007):

As for suicide bombers in particular, almost invariably they are portrayed as genuinely religious people who love jihad more than they love life and fear God more than they fear death. The biographies often detail at length how the 'martyr' used to pray incessantly and spent his time reading the Quran. The bombers are said to have prayed in the mosque, as opposed to praying at home, which is the best option in the eyes of God. They often pray more than the average Muslim, certainly more than is expected of them by God. They also wake up to make their pre-dawn prayers (qiyam), which is not a religious obligation, but a voluntary

expression of devotion. Some are said to have memorized the Quran by heart at a very young age; others fast every Monday and Thursday, when they are not required to do so by religion (although it is part of the Sunna). (pg. 103-104)

On the other hand, we did encounter a few examples suggesting temperate religious practice, such as:

Anas related the story of the three men who asked the Prophet's wives about his worship. When they vowed to pray all night, or fast every day or refuse to marry, the Prophet (PBUH) said: (By Allah, I fear Allah the most and among you I know Him the best, but I fast but not every day, and I pray at night but not all night, and I marry women; whoever does not wish to follow my way, he is not from us)

Quantitative Analysis and Results

We developed a detailed coding scheme based on the results from the qualitative, thematic analysis of the data. As mentioned earlier, we also extracted over 500 excerpts from the collected documents, and then had two raters, working independently, code each excerpt in terms of its metacognitive dimension and valence. We describe the coding scheme and inter-rater reliability next.

Coding and Reliability

1. **Knowledge: Maintenance vs. change (individual or cultural).** This dimension refers to beliefs about the pursuit of knowledge and innovation. Beliefs that encouraged knowledge maintenance were coded as -1 and beliefs that supported knowledge change were coded as +1.

Knowledge Maintenance

- Emphasize the priority and continuance of long-established conceptions of the world and associated practices
- Encourage return to past ways
- Indicate priority of learning traditional doctrine over other forms of knowledge
- Signify that some forms of knowledge are bad/useless

Knowledge Change

- Emphasize the importance of learning, knowledge, knowledge acquisition
- Value of change at the individual or cultural levels
- Indicate existing beliefs may be wrong, incomplete, or no long fit with current situations
- Signify that all knowledge is good

2. **Coherence: Homogeny vs. diversity (individual or cultural).** This dimension refers to beliefs about whether it is acceptable for people to have different beliefs. Ideas that emphasized the importance of homogeny were coded as -1, and ideas that supported diversity of beliefs were coded as +1.

Homogeny

- Emphasize the importance of commonality or consistency of beliefs and knowledge, either in individuals' knowledge bases or, among individuals within communities at various levels of granularity.

Diversity

- Stress the acceptability or even benefit of diversity in beliefs and knowledge at the individual or group level.

3. **Information Exchange: Separation vs. interaction with other groups.** This dimension refers to beliefs concerning religious groups' interactions with non-members, including beliefs that govern the extent and kind of communication with others who may hold different beliefs. Statements that encouraged separation were coded as -1, and statements that encouraged interaction were coded as +1.

Separation

- Members should avoid open communication with non-members
- Communications should be one sided (informing the other)
- Interactions generally negative

Interaction

- Interaction with non-members is acceptable, even encouraged
- Interactions should be positive

4. **Judgment: Authority vs. independence.** This dimension is concerned with who is sanctioned (and responsible) to engage in real thinking, reflection, interpretation, and decision making. Statements that encouraged obedience to judgments made by authorities were coded as -1, and statements that encouraged independence in judgment were coded as +1.

Authority

- Only a selected few should make appraisals and judgments
- Free choice of what religion to belong to (if any) is a bad thing

Independence

- Every member should think for themselves
- Individuals should choose what religion to belong to (if any), no compulsion in religion
- Members ought to formulate their own interpretations of religious texts, as well as how various teachings would apply in given situations.

5. **Deliberation: Polarized vs. balanced.** This dimension indicates the extent to which the writings encourage blind conviction of one's beliefs or more objective thought processes.

Passages that encouraged polarized beliefs or actions were coded as -1, and passages that encouraged balanced deliberation or action were coded as +1.

Polarized

- Emphasize that one way is absolutely, 100% correct or good
- Own goals are paramount, so any actions necessary to achieve goals are reasonable
- Accept any opinions that support ones' desired beliefs/actions

Balanced

- Need to consider all evidence and opinions
- Weigh both pros and cons of actions

6. **Other.** The excerpt does not fit clearly within any of the above categories of metacognitive belief.

As described above, coders also rated the valence of each excerpt assigned to a metacognitive category, as follows:

- a. -1 for maintenance, homogeneity, separation, authority, polarized
- b. 1 for change, diversity, interaction, independence, balanced

We did not assign a valence code to statements coded as "F. Other."

Two raters independently coded the webpage excerpts. Each unit was coded according to one of the five metacognitive ideas expressed in the text, as described above. In addition, the coding also captured the valence of these metacognitive ideas. The coders' initial ratings were used to determine inter-rater agreement. They held meetings to discuss disagreements, and determined the final set of codes by consensus. Cohen's Kappa was used to compute inter-rater reliability for the metacognitive categories, as it takes into account agreement by chance. The inter-rater reliability for metacognitive categories for moderate text was $\kappa = .54$ and $\kappa = .43$ for the extremist text. Both of these numbers fall within the moderate range of reliability (Landis & Koch, 1977). The inter-rater reliability for valence was quite high (99% agreement for moderate text and 97% for extremist text).

Relative Frequency of Metacognitive Categories. The percentage of excerpts assigned to each of the five metacognitive categories is displayed in Figure 2. As in Figure 2, the metacognitive ideas included in moderate texts tended to emphasize knowledge and judgment, followed by information exchange. On the extremist side, information exchange was the most prevalent kind of metacognitive idea discussed, with knowledge and judgment following. Coherence and deliberation were the least frequently used categories for each, and were essentially nonexistent within the moderate documents.

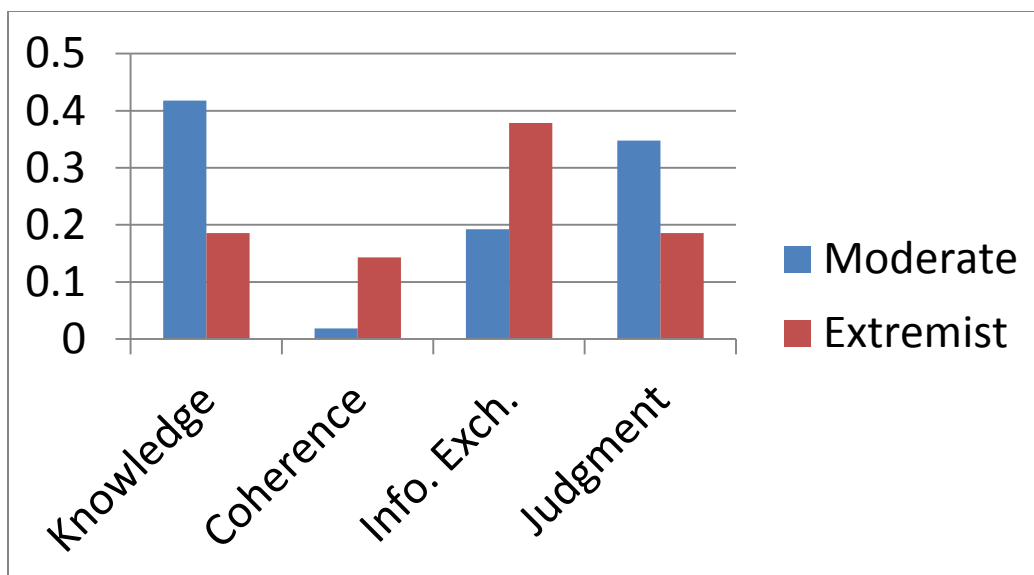


Figure 2. Percentage of excerpts by metacognitive category.

Valence of Each Category. Overall, the average valence for the moderate text was .87, and the average valence for the extremist text was -.42. The variability in metacognitive categories and valence across the moderate and extremist text was significantly greater than chance, $\chi^2(13) = 271.61$, $p < .001$. This indicates that excerpts from moderate websites tended to contain beliefs that encouraged cultural change, diversity of beliefs, interactions between Muslim and non-Muslim groups, independence in judgments, and balanced thought processes. In contrast, excerpts from extremist websites provided more support for knowledge maintenance, homogeneity of beliefs, separation between groups, and obedience to judgments made by authorities. Figure 3 displays the averages of the positively and negatively valenced metacognitive codes for the excerpts from moderate and extremist websites.

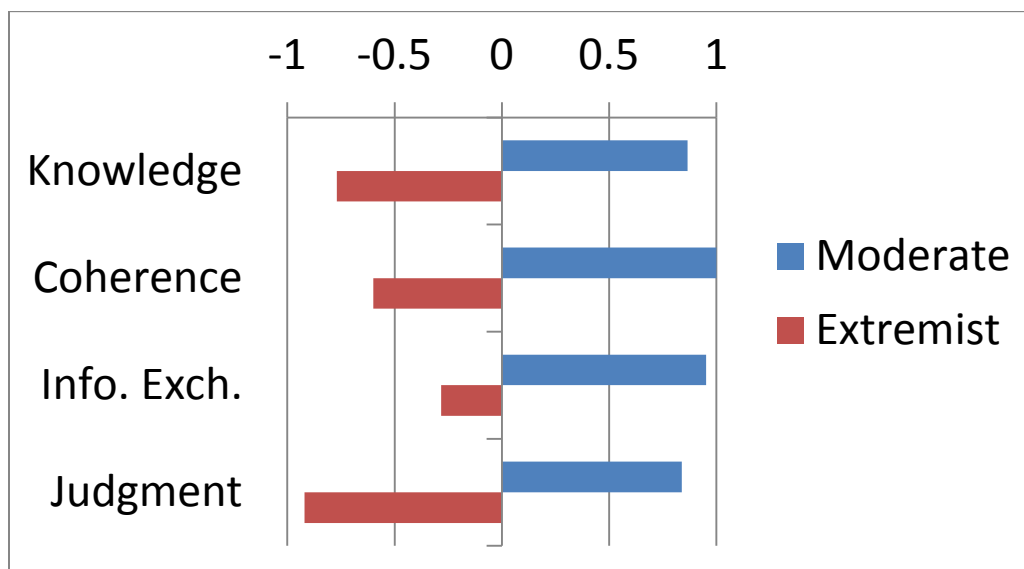


Figure 3. Mean valence by metacognitive category and document type.

A 2 (valence: positive or negative) x 2 (website source: extremist or moderate) contingency chi-square was calculated for each metacognitive dimension in order to determine whether there was a significant difference in the valence of metacognitive beliefs presented on the moderate and extremist websites. These results are described below.

Knowledge: Maintenance vs. change. For the knowledge maintenance vs. change dimension, excerpts from extremist websites (88%) were significantly more likely to support knowledge maintenance than were excerpts from moderate websites (7%), $\chi^2(1) = 71.26, p < .001$. For example, “innovation is misguidance” is an excerpt from an extremist website that encourages knowledge maintenance and abiding by traditions. In contrast, here is an excerpt from a moderate website that support knowledge change: *Religion becomes a dynamic and evolving concept, rooted in history but given various interpretations suited to our times and addressing our problems and challenges.*

Coherence: Homogeny vs. diversity. For the homogeny vs. diversity dimension, excerpts from extremist websites (80%) were significantly more likely to mention support for homogeny of beliefs than were excerpts from moderate websites (0%), $\chi^2(1) = 9.6, p = .002$. Excerpts from extremist websites that supported homogeny of beliefs included statements, such as:

“To accept the idea of pluralism means that you do not care much about religion.”

“The ultimate goal of Jihad in Islam is for no religion to remain on Earth except Islam.”

In contrast, the following excerpts from moderate websites accept and encourage diversity:

“Just as men have invented different languages to talk to each other, so they have invented different religions to talk to God, and God understands them all well enough.”

“In a world as large as Islam, in a history as long as that of Islam, legitimate differences in doctrine and practice and should be expected and appreciated.”

Information exchange: Separation vs. interaction with other groups. For the separation vs. interaction dimension, excerpts from extremist websites (64%) were significantly more likely to support separation between Muslim and non-Muslim groups than were excerpts from moderate websites (2%), $\chi^2(1) = 37.67, p < .001$. Here are examples of excerpts from extremist websites that advocate separation between groups:

“Believing Muslims must keep themselves highly separated from non-believers.”

“Do not pray after a Jew or a Christian, do not eat slaughtered meat from them, do not attend their funerals, and do not take care of their sick.”

The excerpts from moderate websites primarily encouraged interaction between groups:

“Allah does not forbid you (Muslims) to deal justly and kindly with those who have not fought against you in accounts of your religion,”

“The future of Islam depends on...not in hiding or retreating but in reaching out and working with people of other faiths to improve the life of all Muslims and Non-Muslims alike.”

Judgment: Authority vs. independence. For the authority vs. independence dimension, excerpts from extremist websites (96%) were significantly more likely mention that only judgments should be made by authorities than were excerpts from moderate websites (8%), $\chi^2(1) = 68.35, p < .001$. Extremist websites encouraged people to obey judgments made by authority: *“Obey whoever is placed in authority over you,”* and *“the gate of Ijtihad is closed.”* In contrast, excerpts from moderate websites tended to encourage people to form their own judgments: *“It is good to discuss and debate religious ideas and interpretations of the Koran”* and *“Ijtihad (critical thinking to come up with solutions to new problems) should always be available.”*

Deliberation: Polarization vs. balance. For the polarized vs. balanced dimension, excerpts from extremist websites (87%) and moderate websites (100%) both encouraged balanced thought processes and actions. There was not a significant difference in the valence of excerpts from moderate and extremist websites on this dimension, $\chi^2(1) = 0.74, p = .389$. While some extremist websites supported polarized beliefs, such as *“One of the most eloquent symptoms of the moral bankruptcy of Western culture is a certain fashionable attitude toward moral issues, best summarized as: ‘There are no blacks and whites; there are only grays.’”* The majority of moderate and extremist websites encouraged balance thought processes: *“One needs to know of something called balance and justice...people should look for the truth from themselves and from other than them.”*

Model of Metacognitive Values. Based on the results of Study 1, we limited the model of metacognitive values to include the dimensions of knowledge, judgment, coherence, and information exchange. Beyond theoretical appeal, each of these showed promising results in terms of exhibiting distinctive value polarities for documents taken from extremist and moderate websites. Deliberation was eliminated from the model, as it was not found to differ by document source. Figure 4 displays the final model.

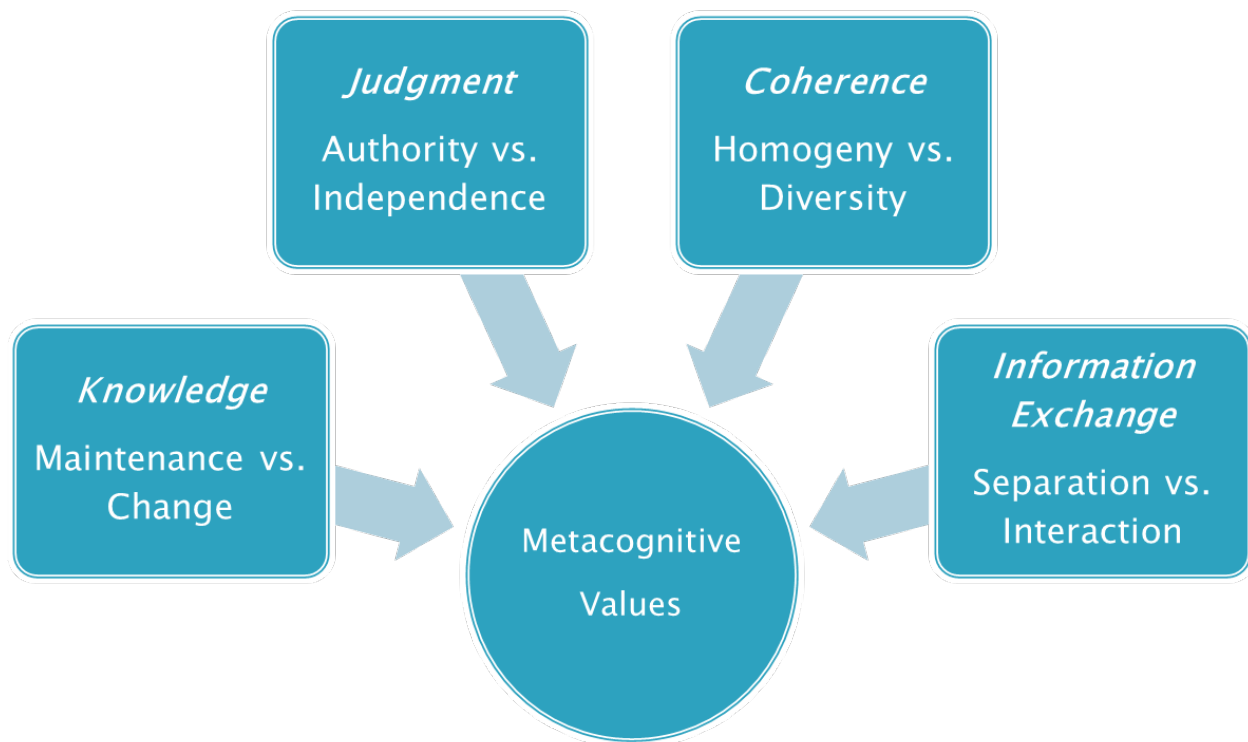


Figure 4. Four Dimension Model of Metacognitive Values embedded in religious ideology.

In Study 2, we seek to further confirm or disconfirm this model by using computational text analysis methods to aid in analyzing the corpus. Such methods remain at an early research phase of development, and suffer from several problems. Most contemporary information extraction approaches for cultural modeling, including lexical co-occurrence methodologies (Bardi, Calogero, & Mullen, 2008), are limited to the recognition of specific entities based on lexical criteria, such as nouns, names of people, places and dates. These include a range of “bottom-up” statistical techniques, such as Latent Dirichlet Allocation (See Appendix B for more details on one such approach; Penta, Shadbolt, Smart, & Sieck, 2011, November). Ontologies, however, can enhance information extraction capabilities by supporting the identification of relations between entities. In Study 2, we exploited this capability, where we describe and utilize ontology representations of the metacognitive ideas in the computational text analyses. The development of this ontology approach for automated measurement of cultural values represents a significant contribution of the current project, and so the background is described in detail prior to revisiting the substantive results related to the metacognitive values model.

STUDY 2: CONFIRMATORY CULTURAL ANALYSIS USING ONTOLOGY-BASED INFORMATION EXTRACTION

In Study 2, we focus on an approach to knowledge extraction that has attracted considerable attention in the knowledge engineering community. This is the approach of Ontology-Based Information Extraction (OBIE; see Wimalasuriya & Dou, 2010). OBIE relies on the exploitation of background knowledge as part of the knowledge extraction process. Unlike bottom-up techniques, it does not strive to identify a set of topics or conceptual categories from a source text. Instead, it starts with a set of predefined knowledge structures (e.g., concepts) and attempts to find instances of these structures in the source text. One of the advantages of OBIE is that it focuses attention on a core set of entities that are relevant to particular problem-solving activity. Thus, whereas bottom-up techniques may yield outputs that have little relevance to cultural analysis, the use of OBIE techniques focuses attention on just those knowledge structures that are relevant to the interests and concerns of a cultural analyst.

As its name suggests, OBIE requires the presence of a domain ontology that can be used by machine-based information extraction processors. The word ‘ontology’ has two meanings. In philosophy, the term is used to refer to the study of the nature of being, existence, or reality. Ontology thus deals with questions concerning the existence of entities, the similarities and differences between entities and the relationships between entities. In computer science, the word ‘ontology’ has a somewhat different meaning. In this case, it denotes an artifact that functions as a representation of the entities in some domain. An ontology could thus be created to represent the entities in domains such as biomedicine or aircraft engineering. In fact, it is probably more appropriate to say that the elements of an ontology represent the human understanding of a domain rather than the entities within a domain. Thus, ontologies serve as external representations of the concepts that humans entertain when talking or thinking about particular things. This makes ontologies suited to represent the knowledge that humans have about a domain. Additionally, because ontologies typically avail themselves of logical formalisms, they are often seen as a means by which human knowledge and understanding can be represented in a machine-accessible format.

A domain ontology thus provides a formal, machine-readable representation of domain knowledge in some target domain, and it therefore supports the exploitation of domain knowledge as part of some automated process (in the case of OBIE the automated process is, of course, the detection, identification and extraction of specific instances of the elements defined in the ontology). The development of a domain ontology is thus a crucial part of the OBIE process. In the following sections, we first present some background on tools and techniques that we reviewed to support OBIE. Then, we provide an overview of the ontology that was developed to support the OBIE process employed in Study 2, which is called the IEXTREME Ontology.

General Approach

OBIE Background. The development of a Web-based knowledge extraction system is based on a decade of research into Ontology-Based Information Extraction (OBIE) systems (see Wimalasuriya & Dou, 2010). This section describes the supporting tools and techniques we reviewed for possible adaptation or extension for use in Study 2.

The first tool considered, MnM,² (Vargas-Vera et al., 2002) is an annotation tool which provides both automated and semi-automated support for annotating web pages with semantic contents. MnM integrates a web browser with an ontology editor and provides open APIs to link to ontology servers and for integrating information extraction tools. There are five main activities supported by the MnM tool. These include:

- Browsing: a specific set of knowledge elements is chosen from a library of knowledge models on an ontology server
- Mark-up: a corpus of documents are manually marked up using the selected knowledge elements
- Learning: a learning algorithm is run over the marked up corpus to learn the extraction rules
- Testing: the IE mechanism is run over the text corpus to assess its precision and recall measures
- Extraction: an IE mechanism is selected and run over a set of documents

A second important tool, OntoMat,³ is a user-friendly interactive Web page annotation tool. It supports the user in creating and maintaining ontology-based semantic annotations. It includes an ontology browser for the exploration of the ontology and instances and a HTML browser that will display the annotated parts of the text. Melita⁴ is an ontology-based text annotation tool. There are two frames in the interface. The left frame is the ontology representing the annotations that can be inserted. A specific color is associated to each node in the ontology. The document to be annotated can be loaded in the right frame. Text can be annotated by selecting text with the mouse, and then clicking on the appropriate node in the ontology pane.

SemanticWord⁵ is an environment based in Microsoft Word that integrates a variety of semantic annotation capabilities. There are two types of annotations in SemanticWord: instance references and triple bags. An instance reference associates a text region with an instance of a class. Triple bags describe the content of a text region with a collection of triples. In this case, the subject of the triple is an instance, the predicate of the triple is a property defined in an ontology, and the object of the triple can be either an instance or a value. The Choosers feature (see Figure 5) of SemanticWord enables triple cells to be filled by dragging and dropping instance references and by picking instances and properties from the Choosers interface. Choosers can use the values already stored in a triple to constrain the lists of choices offered to the user.

² <http://kmi.open.ac.uk/projects/akt/MnM/>

³ <http://annotation.semanticweb.org/ontomat/>

⁴ <http://www.dcs.shef.ac.uk/~alexiei/WebSite/University/Melita/index.html>

⁵ <http://mr.teknowledge.com/DAML>

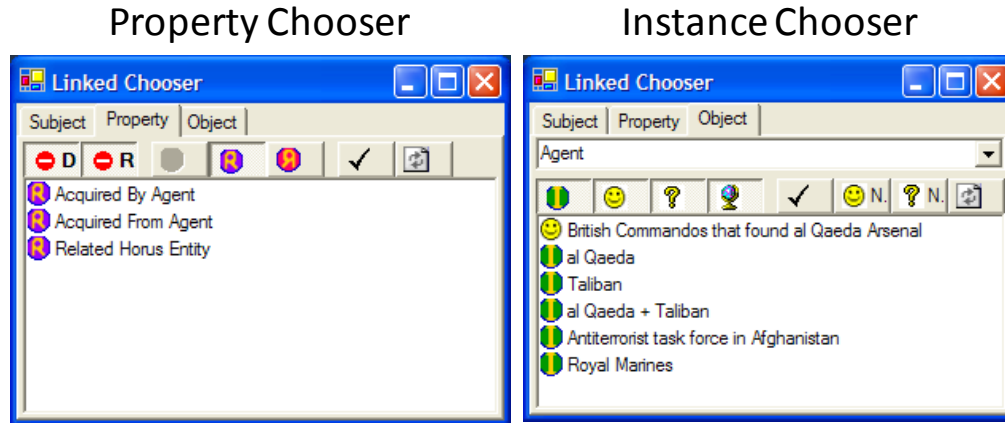


Figure 5. SemanticWord chooser panes.

SemanticWord also provides Personal Class Toolbars for generating both content and annotations together with just one mouse click. Users can create any number of Personal Class Toolbars, each one of them tied to a single class. Each personalized class toolbar contains an instance selection combo box and buttons to create instance references corresponding to the selected instance or a new one. A class cascading menu includes an entry for every named class in the ontology attached to the document. This menu gives users access to most of the operations related to ontology classes, including defining new instances, creating personal class toolbars, and opening instance choosers. When a user executes any of these functions from this menu, the menu entry corresponding to the selected class is duplicated and placed at the top of the menu so the user can access it easily the next time that they needs it. Finally, SemanticWord integrates an information extraction system. As the user types the content of the document, a background thread feeds new or modified text to the information extraction system in paragraph units (roughly), obtains the extracted entities with their position in the text, and underlines those text regions with a blue wiggly line. This procedure resembles Word spelling and grammar checking. The user can examine the extracted entities and convert them into instance reference annotations.

Semantic mark-up is a plug-in to Internet Explorer that supports semantic annotation. When a page is loaded into the Web browser, the plug-in scans the page to see if it contains any existing semantic mark-up. If so, the plug-in identifies the DAML+OIL types, properties, and instances used in that semantic mark-up and it displays a toolbar containing buttons corresponding to these elements. Any semantic annotations found within a page are displayed on the same page as a Semantic Mark-up Table. This shows either the single triple containing the selected concept or all the triples contained in the page.

Amilcare is an adaptive information extraction (IE) system designed to support document annotation within the framework of the semantic web (Ciravegna & Wilks, 2003). It was developed in the context of the AKT initiative and is based on ML technology that generates rules for semantic mark-up of both unstructured (e.g., free text) and structured (e.g., XML/HTML) text sources. Amilcare uses ML technology to generate rules, which are learned by generalizing over a set of examples found in a training corpus annotated with XML elements. Amilcare's ML technology produces two types of rules:

1. Rules that insert semantic annotations into the text, and
2. Rules that correct mistakes and imprecision in the annotations provided by (1).

A tagging rule is composed of a left-hand side containing a pattern of conditions on a connected sequence of words, and a right hand side that is an action inserting an XML element into the text corpus. Amilcare's default architecture includes the connection with Annie, GATE's⁶ shallow IE system, which performs tokenization, part of speech tagging, gazetteer lookup and named entity recognition. The architecture, however, is flexible enough to allow any other pre-processor to connect via the API. The preprocessor is also the only language-dependent module, the rest of the system being language independent (experiments were performed in English and Italian). Amilcare thus provides a platform for automated semantic annotation that is sufficiently flexible to deal with both free text documents and highly structured web resources (e.g., web pages, XML files).

Amilcare works in three modes: training mode, test mode, and production mode. In training mode, Amilcare can be used to learn semantic annotation rules that provide the basis for information extraction. Amilcare is based on the Learning Patterns via Language Processing (LP2) algorithm (Ciravegna, 2001), which is a supervised algorithm that falls into a class of Wrapper Induction Systems using LazyNLP. LP2 induces symbolic rules that insert SGML tags into text by learning from examples in a user-defined tagged corpus. Induction is performed by generalizing from the examples in the corpus. As part of the generalization process, LP2 uses generic shallow knowledge about natural language as provided by a morphological analyzer, a part-of-speech tagger and a gazetteer. The rules generated by LP2 consist of a left-hand side, containing a pattern of conditions on a connected sequence of words, and a right-hand side, which inserts an SGML tag into the source text.

Once the annotation rules have been learned, Amilcare can be used in a test mode. Amilcare is used to test the induced rules on an unseen tagged corpus. By applying the learned rules in this mode, the analyst is able to evaluate how well the system performs. When running in test mode Amilcare first removes all the annotations from the corpus, then re-annotates the corpus using the induced rules. Finally, the results are automatically compared with the original annotations and the results are presented to the user.

The production mode is used when rule learning and evaluation are complete. It annotates new documents using the available rules and makes the annotated documents available for subsequent processing steps, e.g., knowledge extraction and knowledge consolidation. Amilcare has been integrated into a number of other semantic annotation systems, including, MnM, OntoMat and Melita, as described above.

IE systems such as Amilcare can be used to enhance the recognition of entities in a document—for example, that 'Rembrandt' is a person; however, such information is not very useful without the ability to derive the relationships between those entities, e.g., that Rembrandt was born on a certain date and is the creator of particular artworks. Extracting such relations automatically allows us to capture a more complete knowledge to populate the ontology and is essential in

⁶ <http://gate.ac.uk/>

information fusion contexts where relevant information is dispersed across multiple source documents. In order to capture relational information, we exploited the successes of work within the AKT initiative, particularly with respect to systems like Artequakt (Alani, Kim, Millard, Weal, Hall, Lewis, et al., 2003a), which attempts to identify entity relationships using ontology relation declarations and lexical information (“The Protege Axiom Language” 2005).

Artequakt (Alani et al., 2003a; Alani et al., 2003b; Alani et al., 2003c) is a system for ontology-based knowledge extraction that was developed at the University of Southampton as part of the AKT initiative (Shadbolt et al., 2004). It combines the use of a domain ontology with a number of supporting tools and resource, including the general-purpose lexical database WordNet and the GATE NLP system. In this case, GATE is used as a syntactical pattern-matching entity recognizer, and WordNet is used as a supplementary information source in order to identify entities that are not recognized by the GATE system. The aim in Artequakt is to identify and extract knowledge fragments from a set of Web-based textual resources, using both a domain ontology and linguistic resources as background knowledge for the extraction process. The specific steps involved in the knowledge extraction process are detailed below, and Figure 6 illustrates the overall process.

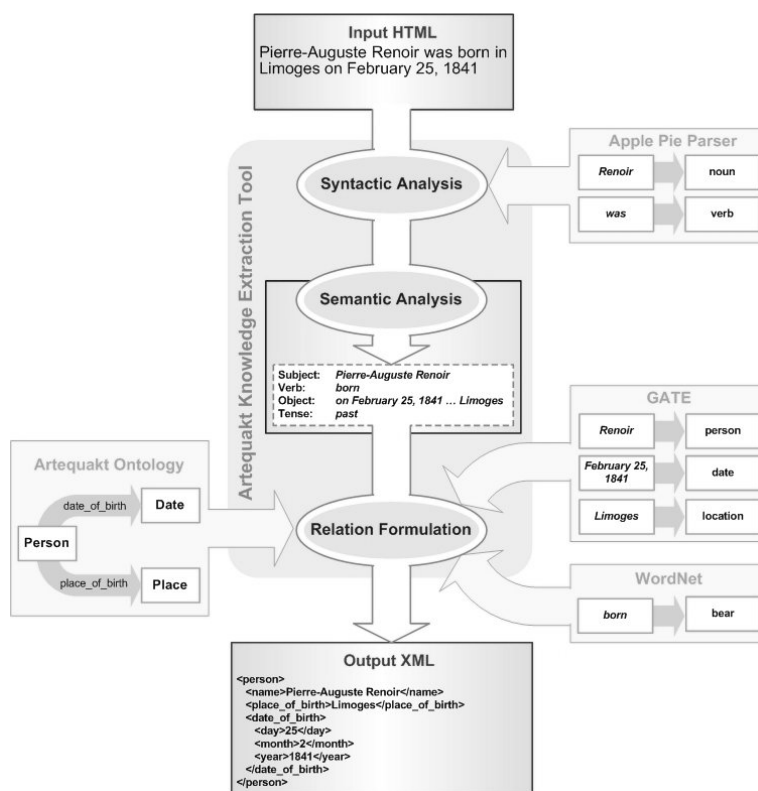


Figure 6. Artequakt's knowledge extraction process.

1. **Syntactic Analysis:** Each Web-based resource (i.e., HTML document) is first subjected to syntactic analysis using the Apple Pie Parser. The Apple Pie Parser is a bottom-up probabilistic chart parser derived from the Penn Tree Bank syntactically-tagged corpus, and it is used in the Artequakt system to generate syntactic annotations of the source text. For example, the parser is used to identify that 'Renoir' is a noun, while 'was' is a verb.

2. **Sentence Decomposition:** The sentences in the Web document are then analyzed and complex/compound sentences are converted into simple sentences. This step is important because relation extraction in Artequakt centers on the analysis of individual sentences.
3. **(Named) Entity Recognition:** GATE and WordNet are then used to identify the named entities mentioned in the text. For example, the system highlights the fact that 'Renoir' is a Person and 'Limoges' is a location). This step is not necessarily independent of the aforementioned syntactic analysis step. In some case, it may be important to know that a specific element corresponds to a noun before it can be identified as a particular type of entity.
4. **Resolution of Anaphoric References:** GATE is used to resolve anaphoric references of singular personal pronouns. For example, a sentence beginning 'He was born...' may be replaced with a sentence beginning 'Pierre-Auguste Renoir was born on...'
5. **Addition of Missing Subjects:** In some cases, the subject for a particular sentence may be missing. This step seeks to identify and add missing subjects where appropriate.
6. **Concept Extraction:** The next step is to establish a mapping between the elements of the domain ontology and the source text. For example, in the case of a sentence that features as its subject the artist 'Renoir,' we want to establish a mapping between the text fragment denoting the artist 'Renoir' and the ontology element (instance) denoting the same artists. To accomplish this, Artequakt engages in an ontology mapping process that takes annotated elements of the source text document and maps them to elements of the domain ontology. In many cases, of course, this process is complicated by the fact that the labels assigned to ontology elements seldom match the corresponding text for a particular entity. As such, Artequakt uses a term expansion technique that uses WordNet-based lexical chains to expand entity names in order to increase the chances of finding a match. For example, GATE identifies 'Museum of Art' as an 'Organization', while the Artequakt ontology defines 'Legal Body' as a general concept for organizations. In order to work out that, with respect to the Artequakt ontology, 'Museum of Art' is a 'Legal Body', Artequakt expands the lexical chains associated with 'Organization' in WordNet and compares these with the labels assigned to elements in the Artequakt ontology.
7. **Relation Extraction:** The final step in the knowledge extraction process is relation extraction. Relation extraction in Artequakt centers on individual sentences. The aim is to extract relationships between a pair of entities within a given sentence. Relations are extracted by matching the verb and entity pairs found in each sentence with relations and concepts pairs as asserted in the domain ontology. As was the case with the concept extraction step, a number of lexical chains (synonyms, hypernyms and hyponyms) from WordNet are used to support the mapping between a text fragment (usually corresponding to a verb) [(e.g., 'born' and an ontology relation (e.g., 'date_of_birth'))]. For the sentence in Figure 6, the main verb, 'born' matches with two relations in the ontology: 'date_of_birth' and 'place_of_birth.' The choice between these two relations in a given sentential context depends on the range of the relation in the ontology and the recognized type of the verb object in the sentence. Thus, 'date_of_birth' is selected when the sentence object is 'February 25, 1841' because this is recognized as a type of 'Date', and the Artequakt ontology specifies that the range of the 'date_of_birth' relation is of type 'Date.' Similarly, when the object of the verb is 'Limoges', then Artequakt selects

the 'place_of_birth' relation. This is because the range of the 'place_of_birth' relation is of type 'Place', and 'Limoges' is correctly recognized as a type of 'Place.'

One of the relatively unique features of the Artequakt system relates to its attempt to extract relational information from unstructured textual resources. Thus, while most knowledge extraction systems focus on the identification of entities in a source text, Artequakt attempts to identify the relations that link various entities together in a coherent semantic network. This is an important aim because much of the knowledge provided by a resource is often contained in the relationships between the entities mentioned in a text. While it might be important to recognize that specific entities, such as a person and an organization, are mentioned in a text, what is often more important is the specific relationship between these entities (such as the fact that the person is a member of the organization). Artequakt attempts to identify these relationships by using the ontology as a background knowledge resource. In particular, the structure of the ontology enables the Artequakt system to establish expectations about the likely set of relationships that might exist between any two entities, and these expectations can guide the analysis of relation-relevant linguistic content. Because this capability provided important background to the technical approach adopted within Study 2, it helps to focus on a concrete example of how the Artequakt approach to relational knowledge extraction extends to application in a cultural analysis context.

Imagine, for the sake of argument that we wish to compile a knowledge base consisting of information about the various groups, organizations and social actors in Afghanistan. Consider the sentence 'The president of Afghanistan is Hamid Karzi.' Following the initial deployment of the aforementioned semantic annotation capability, the sentence is annotated as followed:

The president of <country>Afghanistan</country> is <person>Hamid Karzi</person>.

The annotations here (represented as XML elements) indicate that the text fragments 'Afghanistan' and 'Hamid Karzi' have been identified as instances of the 'Location' and 'Person' classes, respectively (both of these classes are defined in the ontology that was used to train the semantic annotation subsystem). Once the entity annotations have been identified and asserted into the textual resource, the relation extraction component subsystem is provided with a much richer resource than would otherwise have been the case against which ontology-based relation extraction can take place. Importantly, it is only once such annotations are in place, that the real value of the ontology (for the detection and extraction of relationships) can be appreciated. Thus, if we imagine that the ontology containing the aforementioned 'Person' and 'Country' classes also asserts an 'isPresidentOf' relationship between these classes,⁷ then a relation extraction system can establish an expectation or prediction about the nature of the relationship between the person and country instances identified in the above sentence. When this expectation is combined with additional further natural language processing of the sentence, the system will be able to assert the appropriate semantic annotation:

The <isPresidentOf>president of<isPresidentOf> <country>Afghanistan</country> is <person>Hamid Karzi</person>.

⁷This would be represented by asserted the 'Person' class as the domain of the 'isPresidentOf' relationship and the 'Country' class as the range of the relationship.

Obviously, the nature of the natural language processing that performed on the sentence is critical to this relation-based annotation capability. It is not sufficient for a system to form simply an expectation about the kind of relationships that might occur between identified entities; the system also needs to ascertain whether the sentential context is correct. Clearly, the assertion of a particular relationship will only be appropriate in certain sentential contexts. Thus, the 'isPresidentOf' relationship would not be appropriate if the target sentence was 'Hamid Karzi lives in Afghanistan.' In this case, another type of relationship, such as 'isInhabitantOf' would be more appropriate. The decision concerning which relationship (if any) to assert in a particular sentential context is based on a strategy similar to that used in previous research, most notably the Artequakt project (Alani et al., 2003a). Essentially, each relationship in the ontology is associated with a 'synset' in the general-purpose lexical database WordNet (Miller, Beckwith, Fellbaum, Gross, & Miller, 2004). When the relation extraction system executes, it attempts to match the words in a sentence against the WordNet-based linguistic grounding provided for each expected relationship. In addition to representing information about synonyms, the WordNet database also represents hypernymy and hyponymy relationships. Using the WordNet database can support the matching process by avoiding problems due to transliteration.

Relation extraction is widely recognized as a much harder problem than entity extraction. The current state-of-the-art in terms of precision for relation extraction is about 70%, whereas in the case of entity extraction it is somewhere in the region of 90%, at least in restricted knowledge domains (Sarawagi, 2008). In the case of the Artequakt system, Alani et al. (2003c) reported average performance metrics of 85% for precision and 42% for recall for 10 artist relations. These results were obtained from an empirical study that applied the Artequakt knowledge extraction system to 50 Web pages in order to extract knowledge about 5 artists. This study resulted in the generation of 3,000 unique RDF triples, each specifying factual information about the artists in the study. However, the number of triples actually identified by human knowledge engineers across the 50 source documents was 6,071. Given that recall is the number of correct answers the system returns relative to the total number of correct answers that could have been returned, we can infer that the number of correct triples asserted by Artequakt in this study was 2,550 (i.e., 42% of 6071). Since precision is the number of correct answers a system returns relative to the total number of answers actually returned, we can infer that 450 (15% of 3,000) triples returned by the Artequakt system were incorrect.

The base of past research into OBIE supporting tools, techniques and processes that we reviewed was instrumental for the development of an OBIE process to support cultural analysis.

OBIE Process for Cultural Analysis. In Study 2, our approach was to use cultural ontologies to support the extraction of culture-relevant information from the Web. As is common with many OBIE systems, the information extraction process used in Study 2 includes a combination of linguistic information and machine learning techniques in order to recognize and extract information content. A description of the approach to knowledge extraction in Study 2 is presented in Smart, Sieck, & Shadbolt (2011; see Appendix C). Step 1 in the process is to develop an initial qualitative cultural model using a limited set of knowledge sources. Step 2 involves the development of a cultural ontology using the qualitative cultural model as a reference point. This ontology is represented using the Web Ontology Language (OWL), which has emerged as a de facto standard for formal knowledge representation on the WWW. Step 3 is to annotate sample texts manually using the cultural ontology in order to provide a training

corpus for rule learning. In the current context, the LP2 algorithm mediates rule learning, which is a supervised algorithm that has been used to develop a variety of adaptive information extraction and semantic annotation capabilities. Following the development of information extraction rules, Step 4 is to apply the rules to Web resources in order to identify instances of the entities defined in the initial qualitative cultural model. Step 5 consists of the identification and extraction of causal relations. The extraction of causal relationships is a difficult challenge because techniques for information extraction have tended to focus on the extraction of particular entities in a text, rather than the relationships between those entities. We attempt to extract causal relationships using an approach that combines the use of background knowledge in the form of a domain ontology with the general purpose lexical database, WordNet. Finally, in Step 6, the extracted cultural knowledge is integrated, stored, and used to estimate the relative frequencies of the various ideas presented in the initial qualitative cultural model.

OBIE requires the presence of a domain ontology that machine-based information extraction processors can use. A domain ontology provides a formal, machine-readable representation of domain knowledge in some target domain, and it therefore supports the exploitation of domain knowledge as part of some automated process (in the case of OBIE the automated process is, of course, the detection, identification and extraction of specific instances of the elements defined in the ontology). The development of a domain ontology, which we refer to as the “IEXTREME Ontology,” was thus a crucial part of the OBIE process adopted in Study 2, as described next.

IEXTREME Ontology. Ontologies can be created using a variety of different languages; however, the language that is the most widely used at the present time is the Web Ontology Language (OWL; Antoniou & van Harmelen, 2004). OWL emerged as a language for knowledge representation on the World Wide Web in 2004, and the World Wide Web Consortium (W3C) has since sanctioned its use. OWL was selected as the ontology representation language of choice in Study 2 for a number of reasons. First, it ensures compatibility with other ontology engineering efforts that have been undertaken in other areas. Second, OWL is built on top of other technologies, such as RDF (McBride, 2004), which have become de facto standards for data representation on the WWW. Third, due to its popularity, there is extensive support for OWL in terms of ontology development and use. Fourth, OWL avails itself of formalisms that support machine reasoning. Subsumption reasoning, for example, enables a reasoner to compute automatically the taxonomic hierarchy for a set of objects in the absence of an explicit specification of subsumption relationships. Reasoning is of particular use when it comes to developing an ontology; for example, it enables an ontology engineer to delegate much of the modeling activity to the reasoner. Based on an initial characterization of ontology elements we can rely on the reasoner to infer a lot of the structural detail relating to the model. This process is typically referred to as ‘ontology normalization’ and it is an essential ingredient of engineering large-scale ontologies. Another reason why reasoning is important to ontology development concerns the support for logical consistency checking. Modeling the knowledge infrastructure of a domain is a difficult process, typically the preserve of experienced knowledge engineers. Fortunately, OWL is amenable to a variety of logical consistency checks that ensure the logical integrity of the model, and these can help avoid common modeling mistakes.

As with all OWL ontologies, the IEXTREME ontology consists of three types of high-level knowledge structure, namely classes, properties and individuals. Classes represent sets of

individuals that belong together because they share common features or properties. Classes broadly correspond to the notion of a concept in psychology. Properties represent relationships between two individuals or between an individual and a data value. Some examples of properties are hasChild and hasAge. The first of these properties can be used to relate individuals where a parental relationship exists between the individuals. It is an example of an object property in OWL. The second property can be used to specify the age of a given individual. This is example of a datatype property in OWL. Datatype properties are used to link individuals to specific data values. The third type of high-level knowledge structure in OWL is the individual. Individuals correspond to specific instances of the classes defined in the ontology. They represent specific objects in the domain of the ontology.

In order to create the IEXTREME ontology, we first analyzed a set of sentences that contained lexicalizations of metacognitive values. In fact, these same sentences were used to derive the taxonomy of metacognitive values. Some example of these sentences, along with the concepts that eventually appeared in the ontology are presented in Table 1.

Table 1. *Examples of the Source Sentences from which Elements of the IEXTREME Ontology were Derived*

Sentence	Ontology Elements
the ultimate goal of Jihad in Islam is for no religion to remain on Earth except Islam; development of all kinds of knowledge, scientific or otherwise, in the Muslim world;	Jihad; Islam; Goal; Religion MuslimWorld; BodyOfKnowledge; Muslim; ScientificBodyOfKnowledge; KnowledgeOrUnderstanding
Many verses of the Quran asks us to study, ask questions, think critically, reflect and consider;	Koran; ReligiousText; ThinkingOrReasoning; CriticalThinkingOrReasoning; Learning
the prophets said to the unbelieving infidels: Serve Allah, you have no other god but Him;	Infidel; Allah; God; Prophet; Disbeliever; Atheist

The aim of the sentence analysis stage was to derive a list of terms that could be used as the basis for ontology construction. In most cases, the terms were used to create classes that were subsequently organized in a taxonomic hierarchy using the Protégé knowledge editor. To support the process of sentence analysis, we created a tool that enabled us to highlight subsections of each sentence and link these subsections to specific elements (classes, properties, and individuals) of the emerging ontology. Figure 7 shows a screenshot of this tool. The tool proved to be invaluable in terms of indicating why particular ontology elements had been included in the ontology. The tool also proved useful in terms of supporting an analysis of how particular kinds of ontology elements were distributed across various types of source sentence.

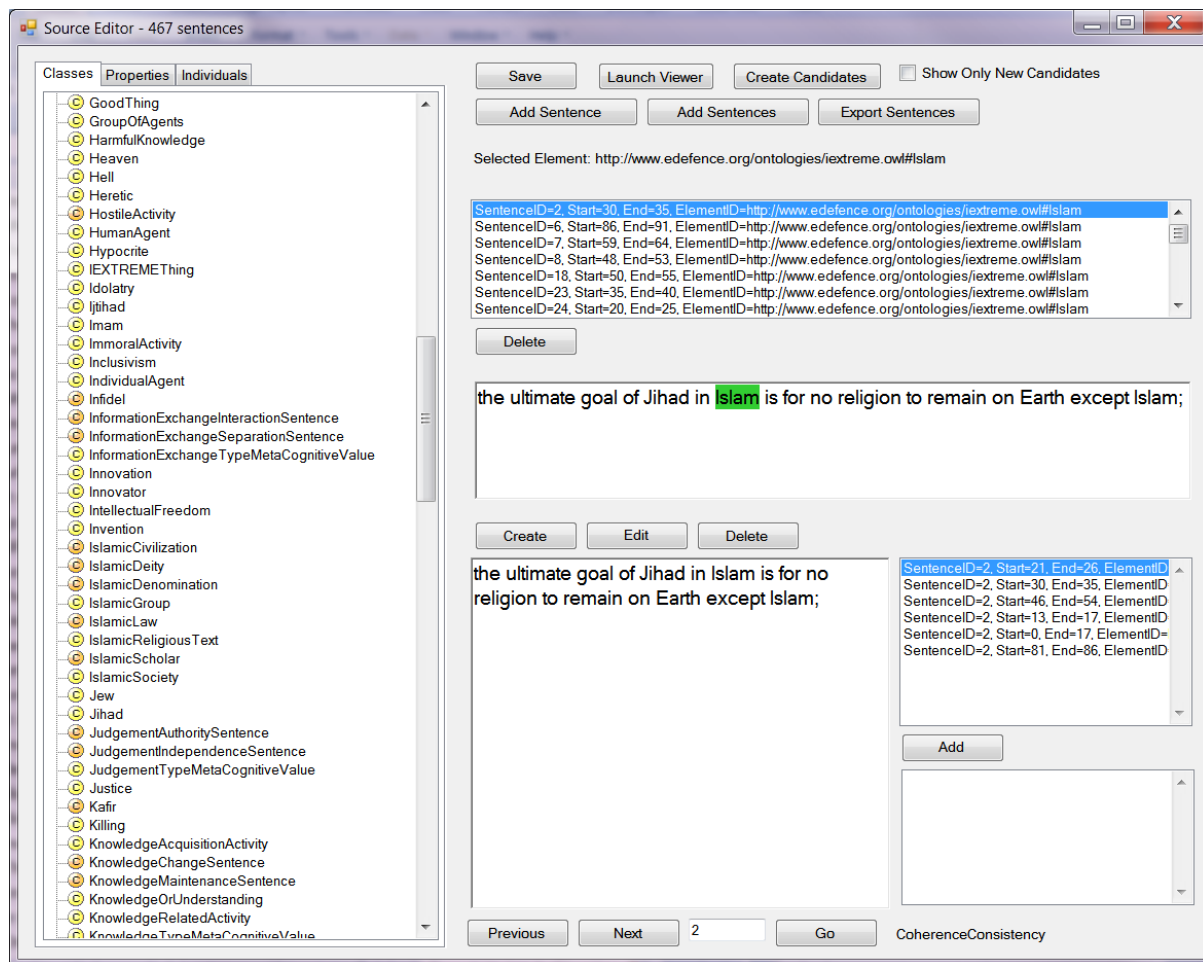


Figure 7. Screenshot of the tool used for analysis of source sentences.

After an initial class hierarchy had been created the ontology was progressively refined and enriched via the addition of elements and axioms. In most cases, this was achieved by referring to online resources such as Wikipedia. The result of this iterative process of sentence analysis, ontology manipulation, and knowledge capture from online resources was the IEXTREME ontology. Figure 8 shows the ontology as it appears in the Protégé knowledge editing tool.

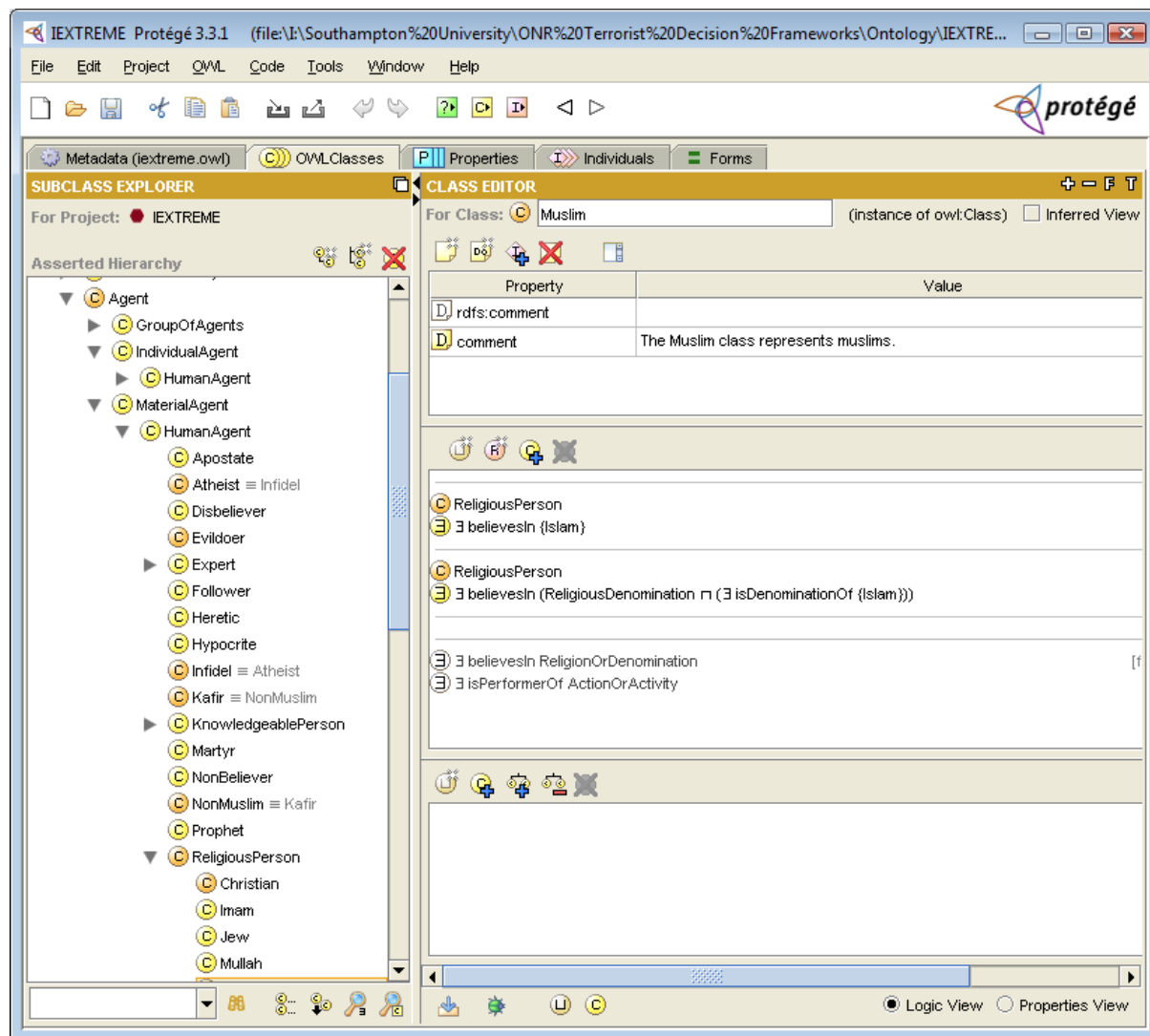


Figure 8. Screenshot of the Protégé knowledge editor showing the IEXTREME ontology.

Ontology Metrics. A number of metrics can be specified for an ontology, such as the number of classes, properties and individuals that are defined. In its basic form, the IEXTREME ontology consists of the following:

- Classes: 741
- Properties: 41
- Individuals: 21
- Triples⁸: 3044

However, other forms of the IEXTREME ontology feature different numbers of elements, specifically individuals and triples. The basic form of the IEXTREME ontology consists of the classes, properties, and individuals that were present at the conclusion of the ontology

⁸ A triple, in this case, refers to an RDF triple, which is an expression of a specific knowledge statement in OWL.

development process; it does not include elements that a reasoner could infer, and which were implicitly specified in the ontology. Alternative forms of the IEXTREME ontology include elements that have been inferred by a reasoner, or which have been automatically asserted based on specific uses of the ontology. In the latter case, for example, the IEXTREME ontology was used to annotate a corpus of the sentences from the collection described above. Since the sentences were already grouped into categories based on whether they expressed one or other metacognitive values, it was hoped that an ontology-based annotation of the sentences might reveal something about the differential frequency of occurrence of specific concepts in textual sources expressing specific metacognitive values. For the purposes of comparison with the basic form of the IEXTREME ontology, the version of the ontology used to support this analysis consisted of the following elements:

- Classes: 741
- Properties: 41
- Individuals: 2,144
- Triples: 12,951

As can be seen from these figures, one of the key differences between this form of the ontology and the basic form concerns the number of individuals and triples in the ontology. The reason for the increase relates to the representation of sentences, semantic annotations, and data generated as part of the analysis. In general, most applications of an ontology will see an increase in the number of individuals and triples rather than any change in the actual classes and properties of the ontology.

Key Concepts. The IEXTREME ontology consists of a variety of classes, each of which can be seen to represent concepts in the domain of religious extremism. The following sections aim to provide a flavor of the kinds of concepts in the ontology. For the purposes of brevity, we focus on just three of the high-level concepts in the ontology, namely actions/activities, agents and metacognitive values.

Actions and Activities. The ActionOrActivity class is a generic class that represents the notion of an action or activity. Within the context of the IEXTREME ontology, it serves as a superclass for a number of other classes; for example, the CognitiveActivity, ConflictActivity, ImmoralActivity, PoliticalActivity, ReligiousActivity and SinfulActivity classes. Each of these subclasses can be further decomposed into other classes. For example, the SinfulActivity class subsumes a number of actions or activities denoting sinful activities. These include Bidah, Blasphemy, Idolatry, and Shirk.

The inclusion of classes representing various types of action or activity allows us to record information about these phenomena in source materials. For example, in the Web page corresponding to the SinfulActivity class, we see three sentences in which the notion of sin is deemed to be expressed (see Figure 9). We can see that two of the sentences are categorized as JudgementAuthority sentences, and the other one is categorized as an InformationExchangeSeparation sentence. Since these sentence categorizations correspond to metacognitive values, we can begin to detect the differential frequency of occurrence of specific concepts across different types of sentences corresponding to one or more metacognitive values.

In essence, this enables us to detect the conceptual markers of specific metacognitive values in source sentences.

The screenshot shows the IEXTREME Ontology 1.0 web interface. The top navigation bar includes links for Home, Classes, Properties, Individuals, and Sentences. The main content area is titled 'SinfulActivity' and provides a description: 'The SinfulActivity class represents sinful activities.' Below this, the 'Facets' section lists the type as 'AKTive8.OWL.Model.OWLNamedClass', indicates it is not deprecated, and provides the URI: 'http://www.edefence.org/ontologies/iextreme.owl#SinfulActivity'. The 'Source Sentences (3)' section contains three bullet points: 'InformationExchangeSeparation: evildoers and vocal sin of all kinds;', 'JudgementAuthority: Democracy is a sin of rights;', and 'JudgementAuthority: spread of sin and shirk the broadest;'. The 'Super Types' section lists 'ActionOrActivity'. The 'Sub Types' section lists 'Bida', 'Bidah', 'Blasphemy', 'Idolatry', and 'Shirk'. The 'Equivalent Classes' section lists 'None'.

Figure 9. Web page showing information about the SinfulActivity class.

Agents. The Agent class represents agents within the IEXTREME ontology. An agent is defined as something that is the performer of a specific action or activity. Thus, we can think of agents as things that do things—that cause specific things to happen. As seen in Figure 10, which illustrates a part of the taxonomic hierarchy associated with the Agent class, the Agent class subsumes a large number of subordinate classes. Most of these classes correspond to various ways of viewing individual agents; for example, as atheists, infidels, martyrs, and so on. However, the class hierarchy also incorporates the notion of spiritual agents, such as deities, and collections of agents, such as organizations, groups, and societies.

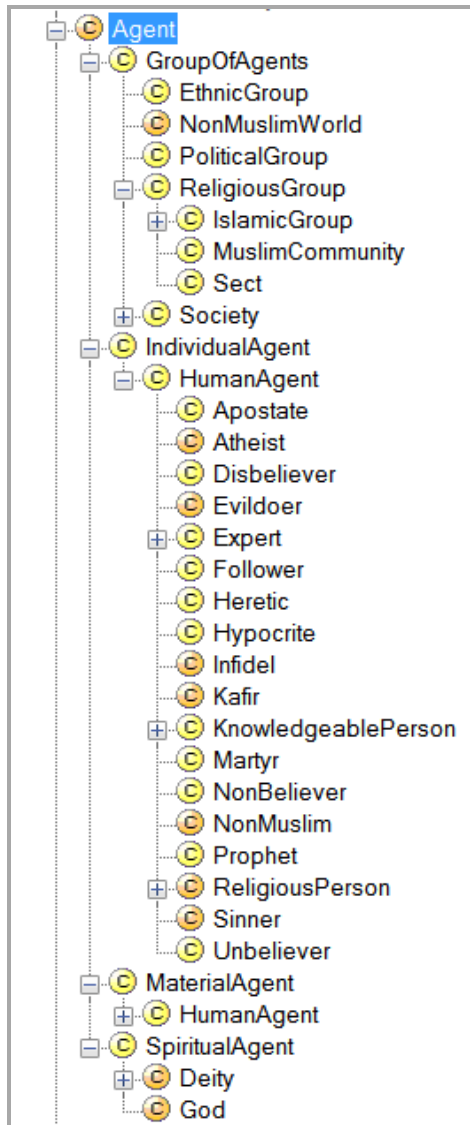


Figure 10. Taxonomic hierarchy associated with the Agent class.

Metacognitive Values. Figure 11 provides a UML projection of the part of the IEXTREME ontology that deals with the representation of metacognitive values (for the purposes of brevity, some of the metacognitive value instances have been omitted). As can be seen from the figure, four types of metacognitive value are represented in the ontology. These are the KnowledgeTypeMetaCognitiveValue, JudgementTypeMetaCognitiveValue, CoherenceTypeMetaCognitiveValue and InformationExchangeTypeMetaCognitiveValue. Specific metacognitive values are represented as individuals that are instantiated from each of these classes. For example, as in Figure 11, both the KnowledgeChangeMeta CognitiveValue and the KnowledgeMaintenanceMetaCognitiveValue represent instances of the KnowledgeTypeMetaCognitiveValue.

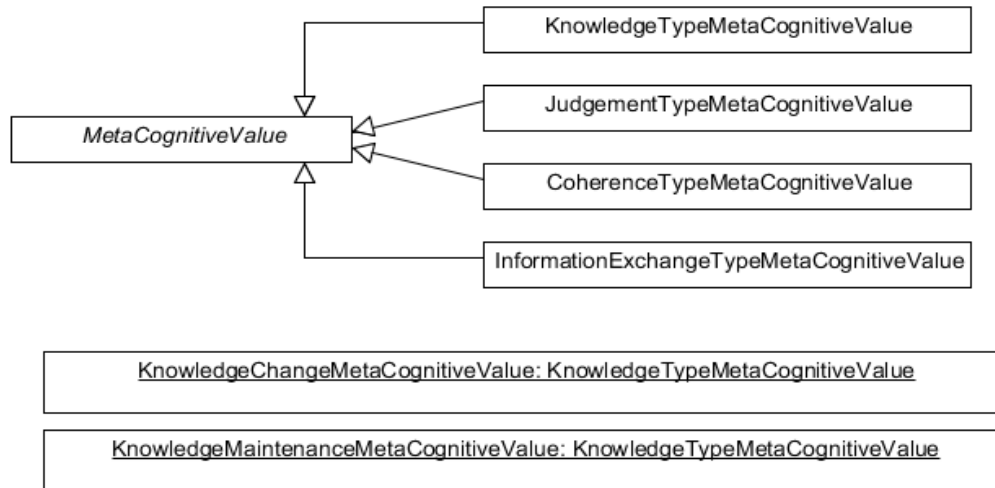


Figure 11. Representation of metacognitive values within the IEXTREME ontology.

One way in which metacognitive values are used in the IEXTREME ontology is to support the classification of resources. Figure 12, for example, shows how metacognitive values are used to support the classification of a particular kind of resource, namely sentences. We can see that a specific sentence is linked to an instance of the SentenceClassification class via the hasClassification property. This instance is then linked to a metacognitive value through the hasClassificationCategory property. The result is that we can represent particular kinds of sentences in terms of their linkage to particular kinds of metacognitive value. A CoherenceConsistencySentence class can be defined, for example, as one that uses logical expressions involving the aforementioned properties in order to make it clear to a machine what is meant by the notion of a sentence that expresses coherence consistency metacognitive values.

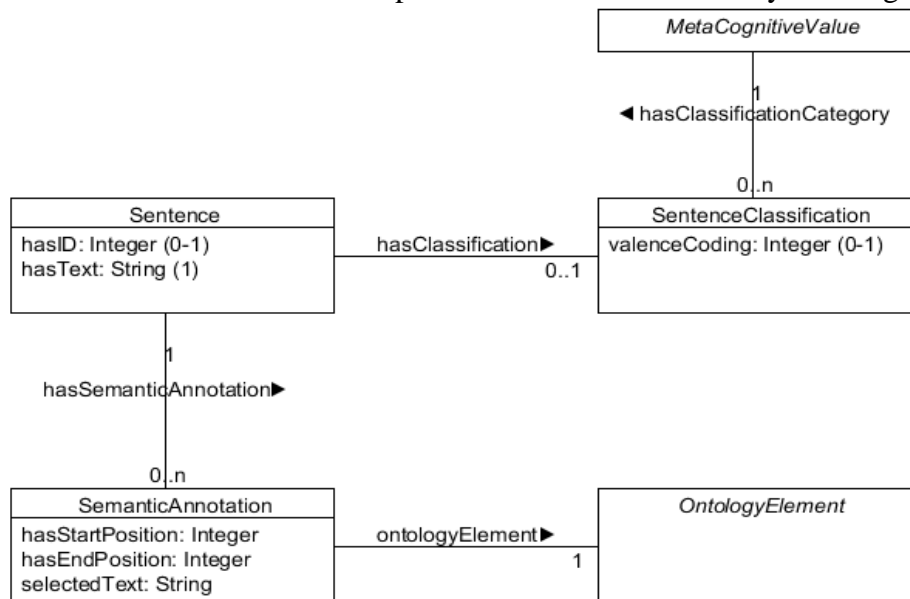


Figure 12. Using metacognitive values to classify resources.

Ontology Viewer Application. In order to support the visualization and evaluation of the IEXTREME ontology, we developed a custom application called the Ontology Viewer Application (OVA; see Figure 13). This application provides a variety of basic visualization and navigation features. For example, it allows the IEXTREME ontology to be viewed as a set of inter-linked web pages. It also enables users to publish the IEXTREME ontology as a set of web pages for independent viewing. More advanced features of the application include the ability to query the ontology contents using the semantic web query language, SPARQL (DuCharme, 2011), the ability to invoke a semantic reasoner to reason over the ontology, and the ability to create rules to customize the reasoning process.

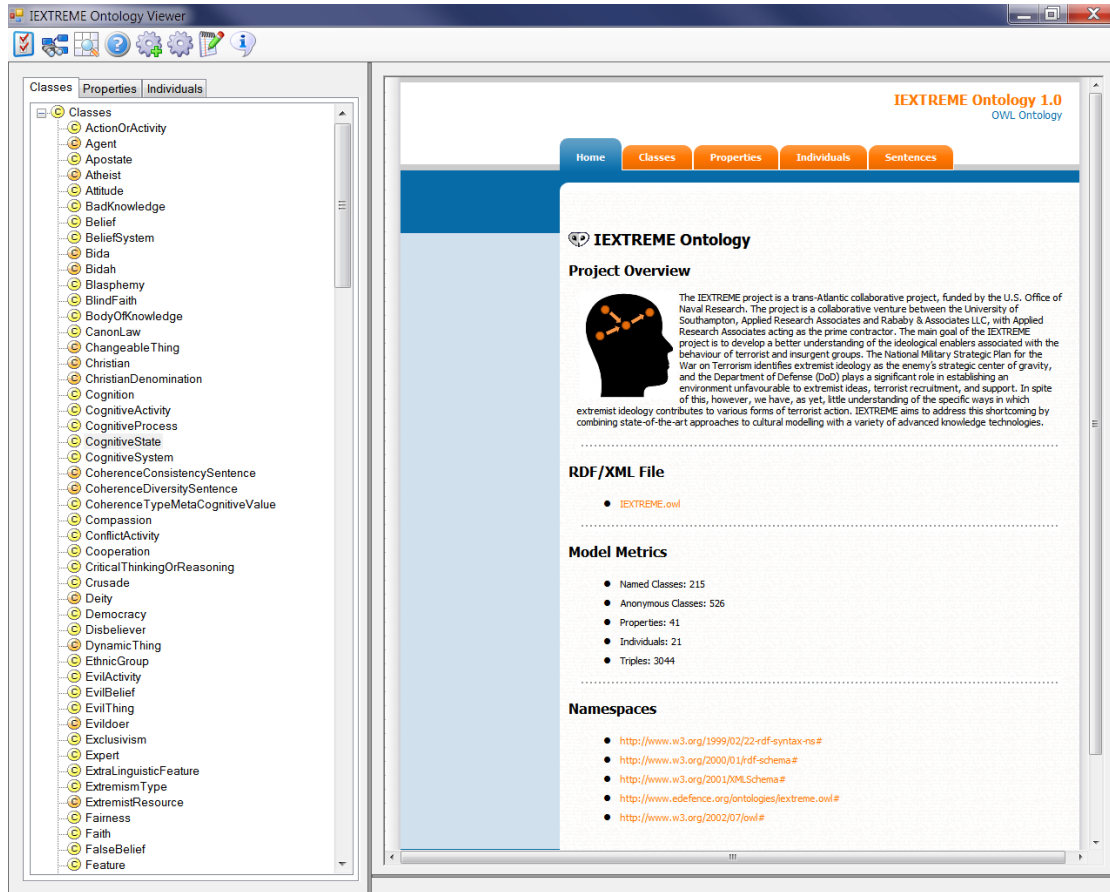


Figure 13. The IEXTREME Ontology Viewer Application.

The functionality of the OVA includes the following:

- **Visualization and Browsing:** The main function of the OVA is to support visualization and browsing of the IEXTREME ontology. The OVA accomplishes this function by providing a Web-based visualization interface to the ontology. The Web-based interface, in this case, is simply a set of Web pages that describes each of the elements in the ontology. Figure 13 shows an example of a Web page showing a specific ontology element.
- **Searching:** The OVA provides a search form, which a user can use to locate specific ontology elements within the ontology.

- **Querying:** The OVA provides capabilities to edit and execute semantic queries defined using the SPARQL query language.⁹ Figure 14 further illustrates the query capabilities of the OVA.
- **Rule Editing:** The OVA provides a Rule Editor Tool, which enables users to create and edit their own rules for the ontology. These rules can be used to support custom reasoning processes.
- **Reasoning:** The OVA provides a Reasoning Tool, which implements a reasoning capability for the IEXTREME Ontology. The query capabilities of the OVA are further illustrated.
- **Publication:** The OVA enables a user to publish the IEXTREME ontology as a set of HTML web pages.

The functionality of the OVA in two specific areas, namely querying and reasoning, is described in the following subsections.

Retrieving Information Using Semantic Queries. One of the capabilities provided by the OVA is the ability to create, edit and execute semantic queries against the IEXTREME ontology. This can be extremely useful because it enables us to ask questions about the structure and content of the ontology.

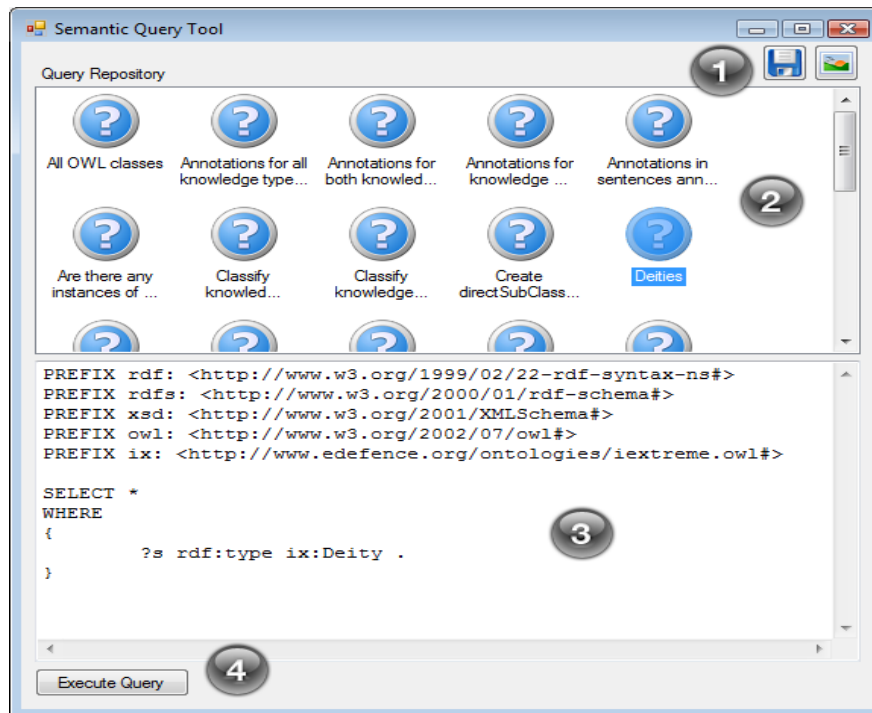


Figure 14. Semantic query tool.

Query capabilities are made available by the OVA through the Semantic Query Tool (see Figure 14). This form comprises a number of interface elements described in Table 2.

⁹<http://www.w3.org/TR/rdf-sparql-query/>

Table 2. *Functionality of the Semantic Query Tool*

Number	Name	Description
1	Toolbar	The Toolbar features two buttons that enable the user to save the contents of the Query Repository (which consists of user-defined semantic queries) and to switch the current view of the Query Repository. Both of these functions are described in more detail below.
2	Query Repository	The Query Repository displays all the semantic queries that have been created by a user of the application. Each query is represented by an icon and a text label—the latter corresponding to the name of the query. When the user selects a query from the Query Repository, the text of the query is displayed in the Query Editor.
3	Query Editor	The Query Editor shows the text of a query which has been selected from the Query Repository. As its name suggests, the Query Editor can be used to edit the syntax of an existing query ¹⁰
4	Execute Button	The Execute Button is used for executing queries that have been selected from the query repository. The results of query execution are shown in a separate dialog box. If the query cannot be interpreted for any reason, the application will throw an exception and an error dialog will be displayed.

A query can be created using the Query Editor component and then executed by clicking the Execute Button. The query shown in Figure 14 is a relatively simple query; it simply asks what types of deities have been asserted in the ontology. If we click the Execute Button while this query appears in the Query Editor, then we see the results shown in Figure 15. These results tell us that there are three types of deity asserted in the ontology: Allah, ChristianGod, and JewishGod

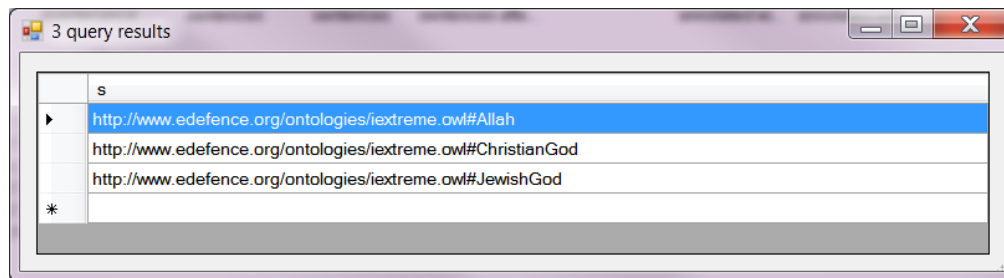


Figure 15. Query results for deities query.

¹⁰Note that the Semantic Query Tool only supports SPARQL queries; other types of query language are not supported. More information about the SPARQL query language can be found on the SPARQL website (<http://www.w3.org/TR/rdf-sparql-query/>).

We can also use queries to pose questions that are more complex. Thus, consider the following query:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX ix: <http://www.edefence.org/ontologies/iextreme.owl#>
```

```
SELECT (str(?text) AS ?result)
WHERE
{
    ?sentence rdf:type ix:Sentence .
    ?sentence ix:hasSemanticAnnotation ?anno .
    ?sentence ix:hasText ?text .
    {
        {
            ?anno ix:ontologyElement ?element .
            ?element rdfs:subClassOf ix:SinfuActivity .
        }
        UNION
        {
            ?anno ix:ontologyElement ix:SinfuActivity .
        }
        UNION
        {
            ?anno ix:ontologyElement ?element .
            ?element rdf:type ix:SinfuActivity .
        }
    }
}
```

This query is clearly much more complex than the previous one. In this case, it is asking about the sentences that mention things related to sinful activities. Essentially, it is retrieving the text of sentences that are annotated with three kinds of ontology element:

- elements that are subclasses of the SinfuActivity class,
- elements that are the SinfuActivity class, and
- elements that are instances of the SinfuActivity class.

If we execute this query, we see the query results listed in Figure 16.

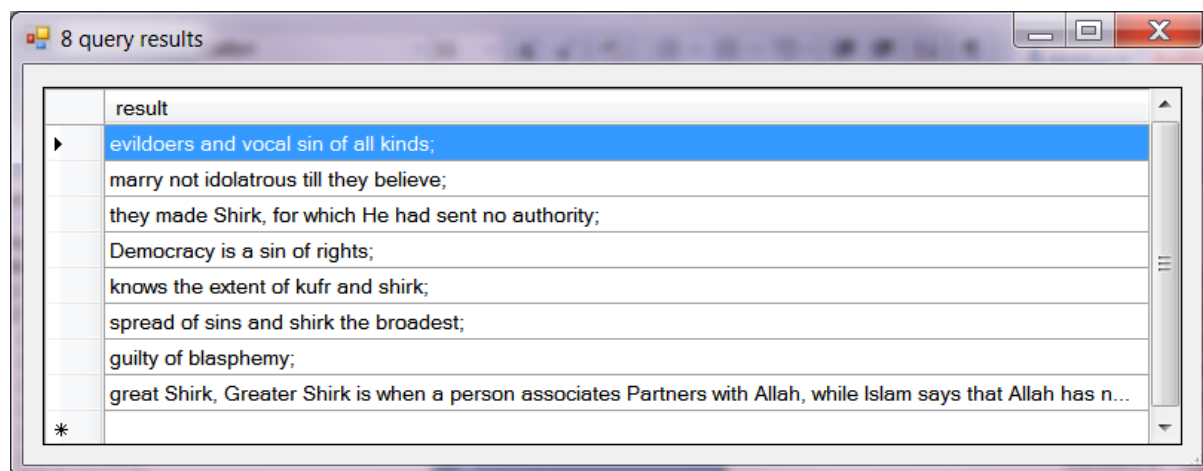


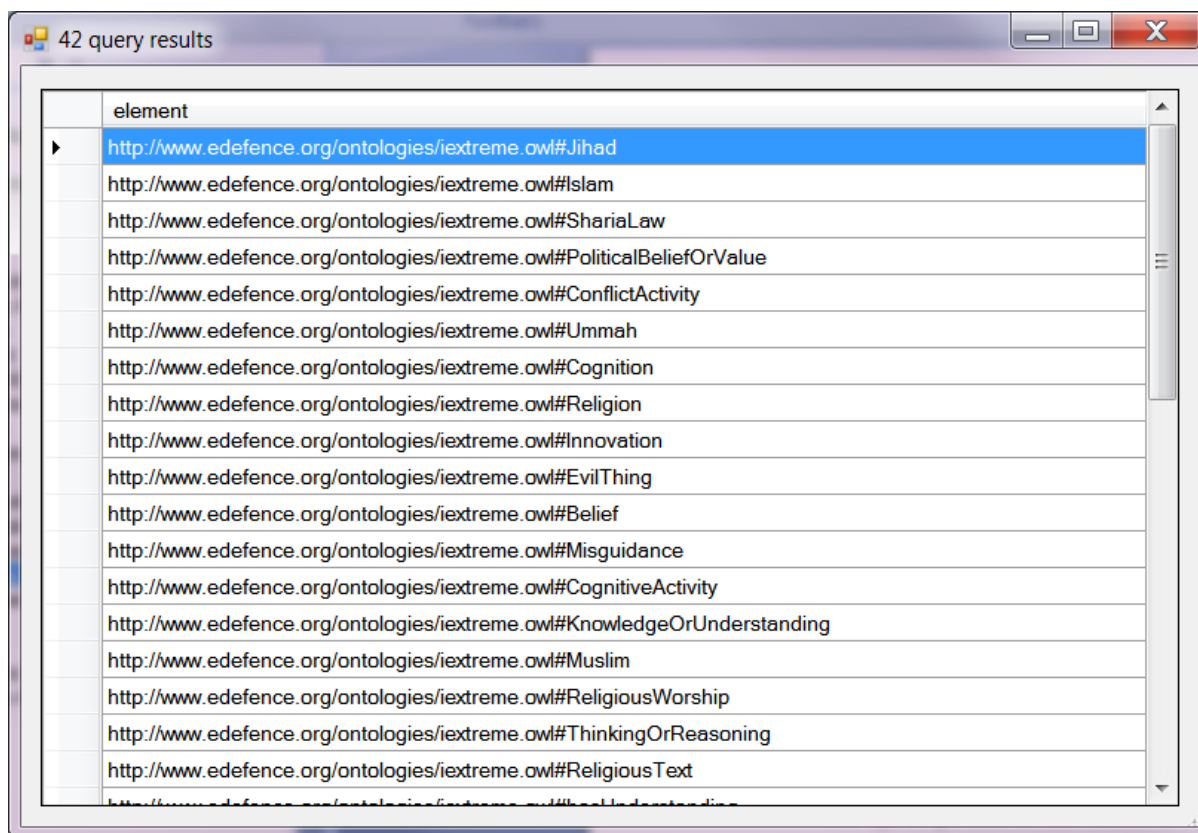
Figure 16. Query results for sentences expressing sinful activities query.

Next, consider the query illustrated below:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX ix: <http://www.edefence.org/ontologies/iextreme.owl#>
```

```
SELECT DISTINCT ?element
WHERE
{
    ?sentence rdf:type ix:Sentence .
    ?sentence ix:hasClassification ?sc .
    ?sc rdf:type ix:SentenceClassification .
    ?sc ix:hasClassificationCategory ix:KnowledgeMaintenanceMetaCognitiveValue .
    ?sentence ix:hasSemanticAnnotation ?anno .
    ?anno ix:ontologyElement ?element .
}
```

This query retrieves all the ontology elements that are used to annotate sentences that express knowledge maintenance metacognitive values. Queries of this kind tell us something about the kind of conceptualizations used in different kinds of sentences. Figure 17 illustrates the results of this query.



element
http://www.edefence.org/ontologies/iextreme.owl#Jihad
http://www.edefence.org/ontologies/iextreme.owl#Islam
http://www.edefence.org/ontologies/iextreme.owl#ShariaLaw
http://www.edefence.org/ontologies/iextreme.owl#PoliticalBeliefOrValue
http://www.edefence.org/ontologies/iextreme.owl#ConflictActivity
http://www.edefence.org/ontologies/iextreme.owl#Ummah
http://www.edefence.org/ontologies/iextreme.owl#Cognition
http://www.edefence.org/ontologies/iextreme.owl#Religion
http://www.edefence.org/ontologies/iextreme.owl#Innovation
http://www.edefence.org/ontologies/iextreme.owl#EvilThing
http://www.edefence.org/ontologies/iextreme.owl#Belief
http://www.edefence.org/ontologies/iextreme.owl#Misguidance
http://www.edefence.org/ontologies/iextreme.owl#CognitiveActivity
http://www.edefence.org/ontologies/iextreme.owl#KnowledgeOrUnderstanding
http://www.edefence.org/ontologies/iextreme.owl#Muslim
http://www.edefence.org/ontologies/iextreme.owl#ReligiousWorship
http://www.edefence.org/ontologies/iextreme.owl#ThinkingOrReasoning
http://www.edefence.org/ontologies/iextreme.owl#ReligiousText

Figure 17. Query results for ontology elements associated with Knowledge Maintenance Sentences Query.

Finally, consider the query below:

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX ix: <http://www.edefence.org/ontologies/iextreme.owl#>
```

```
SELECT DISTINCT (str(?text) AS ?result)
WHERE
{
    ?anno ix:ontologyElement ix:KnowledgeOrUnderstanding .
    ?anno a ix:SemanticAnnotation .
    ?anno ix:selectedText ?text .
}
```

This query asks for the text associated with a specific kind of semantic annotation, namely one that features the KnowledgeOrUnderstanding class, to be returned. If we execute this query, we see the query results listed in Figure 18.

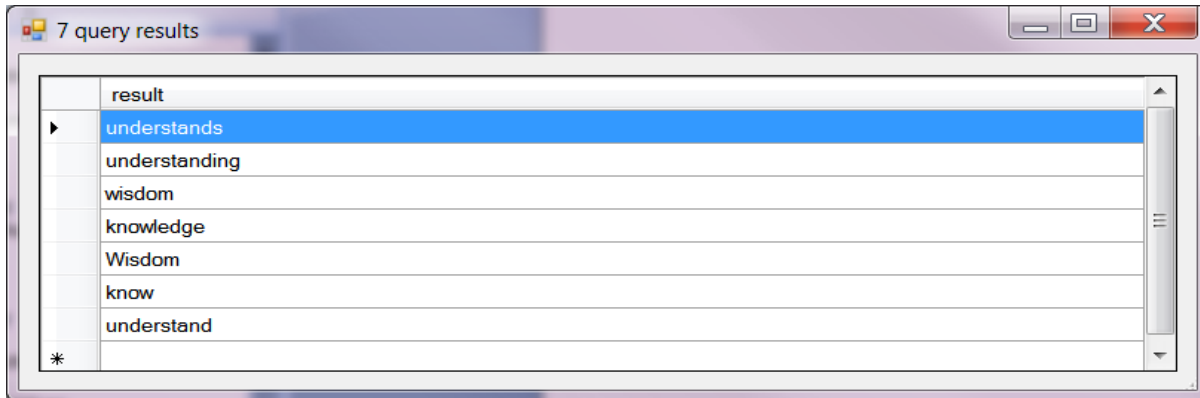


Figure 18. Query results for the text associated with semantic annotations using the KnowledgeOrUnderstanding class query.

Rule-Based Reasoning. In addition to a querying capability, the OVA also provides an ability to create, edit and execute rules. These rules can be used to implement sophisticated forms of inference that exploit the semantic infrastructure of the IEXTREME ontology. As an example of this inferential capability consider a rule designed to classify automatically sentences as instances of a class called the KnowledgeMaintenanceSentence class. The syntax of this rule is presented in Figure 19.

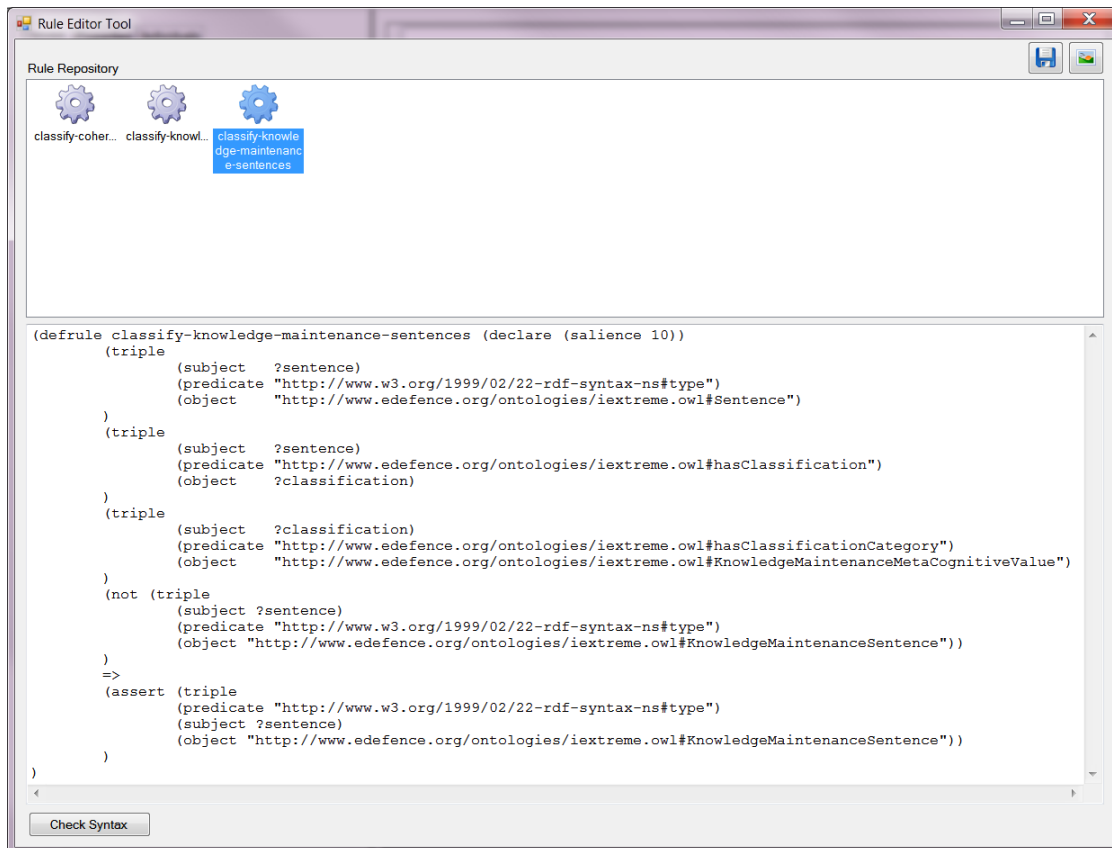


Figure 19. Rule Editor Tool showing 'classify-knowledge-maintenance-sentences' rule.

This rule (and indeed all rules in the OVA) is implemented as a CLIPS rule using the ‘defrule’ construct.¹¹ Each rule features a set of conditions in the left-hand side rule, which are matched against the triples in the ontology. If the conditions of the rule are satisfied, then the statements on the right-hand side or ‘action’ part of the rule are executed. In general, the action part of the rule contains statements that assert new triples into the ontology. Thus, the rule in Figure 19 executes (or ‘fires’) when the following conditions are met:

- there is a triple x which has ‘<http://www.w3.org/2000/01/rdf-schema#subPropertyOf>’ as its predicate
- the subject of x is the predicate of another triple y , which also has a subject a and an object b
- there is no triple which has the object of x as its predicate and in which a and b are the subjects of objects, respectively, of the triple

The action part of this rule asserts a triple, which has a predicate corresponding to the object of x , a subject corresponding to a and an object corresponding to b . The rule essentially adds triples representing the fact that two objects linked by a property z must also be linked by any properties that are super properties of z . For example, if we have two properties, `isParentOf` and `isFatherOf`, and `isFatherOf` is a subproperty of `isParentOf`, and we also have two instances, Bill and Peter, where Bill is linked to Peter via the `isFatherOf` property, then a reasoner should be able to infer that Bill is also a parent of Peter and assert that Bill `isParentOf` Peter. When asked whether Bill is a parent of Peter, an intelligent machine should be able to draw on the semantics of the ontology to infer that Bill is indeed a parent of Peter and, therefore, give a semantically-sensible response to the question posed to it.

Once a rule has been defined, a reasoner can use it to perform inferences against the IEXTREME ontology. This is accomplished within the OVA by using the Reasoning Tool (see Figure 20). The Reasoning Tool allows a user to execute the rules created by the Rule Editor Tool and then it adds whatever knowledge statements the reasoner inferred to the IEXTREME ontology. This capability can enrich the ontology in various ways. For example, once the ‘classify-knowledge-maintenance-sentences’ rule shown in Figure 19 is executed by the reasoner, then the syntactic complexity of semantic queries involving `KnowledgeChangeSentences` can be simplified considerably. Recall, for instance, the query used to retrieve the ontology elements used in semantic annotations of sentences expressing knowledge maintenance metacognitive values. The original version of the query was as follows:

¹¹ More information about the CLIPS language can be found on the CLIPS website (<http://clipsrules.sourceforge.net/>).

PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX ix: <http://www.edefence.org/ontologies/iextreme.owl#>

```
SELECT DISTINCT ?element
WHERE
{
    ?sentence rdf:type ix:Sentence .
    ?sentence ix:hasClassification ?sc .
    ?sc rdf:type ix:SentenceClassification .
        ?sc ix:hasClassificationCategory ix:KnowledgeMaintenanceMetaCognitiveValue
        .
    ?sentence ix:hasSemanticAnnotation ?anno .
    ?anno ix:ontologyElement ?element .
}
```

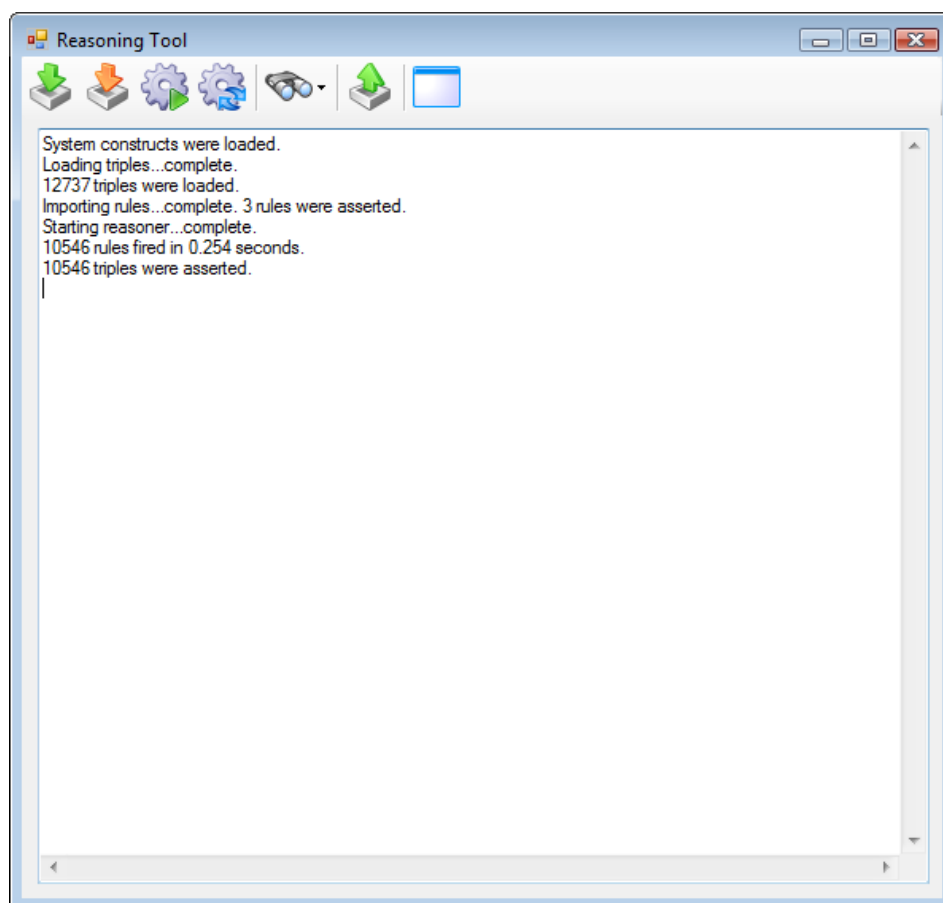


Figure 20. The OVA Reasoning Tool.

Now, following the execution of the ‘classify-knowledge-maintenance-sentences’ rule, the syntax of this query can be simplified to the following:

Using the Ontology to Annotate Source Sentences. As mentioned in previous sections, the IEXTREME Ontology has been used to support the analysis of a set of source sentences that were used as part of the derivation of metacognitive values at an earlier stage of the project. These sentences were originally taken from the set of religious (Islamic) textual resources as described in Study 1, and they each reflect the expression of a specific kind of metacognitive value. Tables 3 shows some examples of these sentences.

PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
 PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
 PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
 PREFIX owl: <http://www.w3.org/2002/07/owl#>
 PREFIX ix: <http://www.edefence.org/ontologies/iextreme.owl#>

```
SELECT DISTINCT ?element
WHERE
{
    ?sentence rdf:type ix:KnowledgeMaintenanceSentence .
    ?sentence ix:hasSemanticAnnotation ?anno .
    ?anno ix:ontologyElement ?element .
}
```

Table 3. *Examples of Sentences Expressing Different Kinds of Metacognitive Value*

Metacognitive Value	Example Sentences
Coherence Consistency (CC)	To accept the idea of pluralism means that you do not care much about religion. The ultimate goal of Jihad in Islam is for no religion to remain on Earth except Islam. The union between monotheism and polytheism is very evil.
Coherence Diversity (CD)	Just as men have invented different languages to talk to each other, so they have invented different religions to talk to God, and God understands them all well enough.
Information Exchange Interaction (IEI)	By facilitating our relations with Non-Muslims then we reflect a brighter picture of Islam and Muslims. A Muslim is allowed to marry a non-Muslim, Christian or Jew, and should give her the liberty to practice her religion without interfering.
Information Exchange Separation (IES)	Fight those who believe not in Allah nor the Last Day. Jihad alone that liberates the Muslim lands from the grip of the unbelievers.
Judgment Authority (JA)	The right to understand and explain Islam is confined to Muslim jurists.
Judgment Independence (JI)	Islam has no generally accepted clerical hierarchy or bureaucratic organization. Ijtihad can be a tool for understanding Islamic principles in a way that fits the needs and challenges of individuals and societies.
Knowledge Change (KC)	Our views should change to reflect our understanding of new knowledge or experience or different circumstances. Seek knowledge by even going to China, for seeking knowledge is incumbent on every Muslim.
Knowledge Maintenance (KM)	Every innovation is misguidance and every misguidance is in the fire. He who learns knowledge for other than God, and his aim be other than God, will abide in fire.

In total, there were 467 sentences grouped into 1 of 8 categories of metacognitive values. In order to better understand how the concepts in the IEXTREME ontology were distributed across these sentences (and thus to better understand the conceptual markers of metacognitive values), we used the IEXTREME Ontology to semantically annotate all 467 sentences.

The results of the analysis show how many times various elements in the ontology appear in the different types of sentences. For example, the notion of Allah has the following distribution pattern across the sentences:

- Coherence Consistency Sentences: 5
- Coherence Diversity Sentences: 0
- Information Exchange Interaction Sentences: 4
- Information Exchange Separation Sentences: 4
- Judgment Authority Sentences: 8
- Judgment Independence Sentences: 5
- Knowledge Change Sentences: 2
- Knowledge Maintenance Sentences: 1

From this distribution pattern, we can see that the notion of Allah does not tend to discriminate between the various kinds of sentences: it has a rather uniform distribution across the sentence categories, and thus its power as a discriminative feature for sentence classification is pretty poor. In contrast to this, consider the notion of a body or system of knowledge, which is represented in the IEXTREME ontology via the BodyOfKnowledge class. This concept has the following sentence distribution profile:

- Coherence Consistency Sentences: 0
- Coherence Diversity Sentences: 0
- Information Exchange Interaction Sentences: 0
- Information Exchange Separation Sentences: 0
- Judgment Authority Sentences: 0
- Judgment Independence Sentences: 0
- Knowledge Change Sentences: 36
- Knowledge Maintenance Sentences: 22

Here we see that the distribution profile of the BodyOfKnowledge concept is not uniform across the sentence categories; instead, it only appears in the Knowledge Change and Knowledge Maintenance sentences. As a result, we can say that the BodyOfKnowledge concept has the potential to discriminate knowledge change and knowledge maintenance metacognitive values. In other words, it may serve as a conceptual marker for these types of metacognitive values in novel sentences.

In general, the results of sentence-based analysis indicate that a number of ontology elements may serve as important discriminative features for the identification of specific metacognitive values. Table 4 lists these elements, which shows how a number of ontology elements may help to discriminate particular types of metacognitive value.

Table 4. *Table Showing Discriminative Potential of a Subset of Ontology Elements*

Ontology Element	CC	CD	IEI	IES	JA	JI	KC	KM
BodyOfKnowledge							●	●
CriticalThinkingOrReasoning						●		
Fighting				●				
FreedomOfChoice						●		
FreedomOfExpression						●		
Ijtihad					●	●		
Innovation							●	●
KnowledgeAcquisitionActivity							●	
KnowledgeOrUnderstanding							●	●
Learning							●	
LogicalThinking						●		
Marriage			●	●				
Misguidance								●
NewThing							●	●
NonMuslim			●					
Peace			●					
Pilgrimage							●	
RationalThinking					●	●		
Relationship			●					
ReligiousScholar						●		
SacredLaw							●	●
ScientificBodyOfKnowledge							●	
Sect			●	●				
Shirk					●			
ThinkingOrReasoning						●		
ToleranceAttitude			●					
Ummah								●
UsefulKnowledge								●
UselessKnowledge								●
ValuedThing							●	●

On the basis of this analysis, it seems that Coherence Consistency and Coherence Diversity values may be the most difficult to identify using ontology-based forms of analysis. This section has provided an overview of the IEXTREME Ontology developed to support OBIE in the context of Study 2. The structure and content of the ontology has been presented, and a specific use of the ontology to annotate sentences from religious texts has been described. Furthermore, an application, which was developed to support the browsing and visualization of the IEXTREME ontology, has been described, and some of the more advanced features of this application (most notably its querying and reasoning capabilities) have been discussed. In the next section, we describe the specific Study 2 methods used to incorporate the IEXTREME ontology as a component of the overall OBIE analysis approach to extract and measure metacognitive values in the source documents.

Method

In this section, we describe the text analysis methodology that was used to process religious text data in order to measure the extreme and moderate sentiments referred to the dimensions introduced in the previous section. The main idea of the proposed approach is to measure what we called the “polarity” of the input text fragments based on the semantic comparison of triples extracted from the input documents. We will give much more detail on what we mean for “polarity” and “triples” in the next sections. This approach requires that part of the original dataset is used to train our model. The method follows the process flow illustrated in Figure 21.

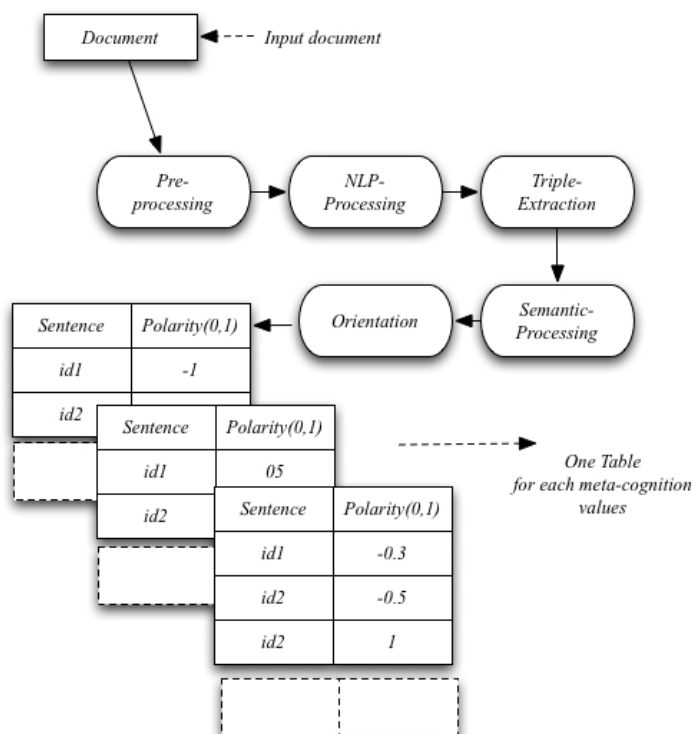


Figure 21. Process flow of our approach.

Step 1: Pre-Processing. In this step, the input document was split into a set of sentences. The sentence splitter is based on the OpenNLP system.¹² For each sentence, a feature vector was built and it was used as input into a classifier in order to determine if the sentence was relevant to the analysis. The feature vector, in this case, was computed using the Bag of Words model, and the method used to assign the values of the vector was a frequency-based one (Manning, Raghavan, & Schtze, 2008). In particular, we used the $tf(t,s) * idf(t,s)$ value, where $tf(t,s) = f(s,t) / |N|$ is the frequency of the term t in the sentence s , $|N|$ is the cardinality of our vocabulary and $idf(t,s) = \log(|S| / f(t,d))$ the inverse document frequency, yielding a measure of the rate between the number of selected sentences ($|S|$) and the frequency of sentences in which the term t appears ($f(t,d)$). The classifier corresponded to a Decision Tree based on the C4.5 algorithm (Quinlan, 1993).

Step 2: NLP Processing. In this step, each sentence was processed in order to extract metadata that was used in subsequent steps. In particular, we implemented a classical tokenization procedure, and for each token, we computed Part of Speech (POS) tags. After this stage, we eliminated stop word tokens that appeared on a predefined Stop Word lists. We built a stop words list based on the ones made in Stanford Library.¹³ POS tags were computed using the Stanford NLP tagger, made available from the same website. We also computed the lemma of each token based on the morphological analysis offered by Stanford Library. Token lemmatization enabled us to process tokens in a similar fashion irrespective of their plural, comparative, and superlative forms.

Step 2: Triple Extraction. In this step, we extracted a set of triples from each sentence. This phase is used to compute what we defined as “polarity” of triples. The polarity of a triple is the numeric measure used to weight the triple respect to the metacognitive values described in Study 1.

The polarity of a triple gives information of the distribution of the cultural values within the text from which the triple is extracted. A triple is defined as (S;V;O) structure, where S is the set of tokens that plays the role of subject, V is the set of tokens that plays the role of verb, and O is the set of tokens that plays the role of objects. The triples are extracted using the following pattern:

$$(N|A)^* - (V|P)^* - (N|A)^*$$

where N is a proper noun, a noun, a personal pronoun or foreign word; A is an adjective; V is a verb that can be in past, past particle, base or gerund forms; and P is an adverb, particle, preposition or conjunction. Here, the pattern is expressed following the regular expression syntax, in fact the symbol $(-)^*$ is used to indicate that the related sub patterns can be matched zero or multiple times and $(|)$ is represents an ‘or’ condition. For each sentence, we can extract different triples by using the position of the next token tagged as V. For the sake of clarity, let us consider how we extract two successive triples. Let us suppose that we have found a set of tokens that matches the pattern described above and then we meet a token classified as V. In that case, we generate a new triple where the tokens that belong to the previous O fill the new set S. This simple rule has some exceptions, which are as follows:

¹² <http://incubator.apache.org/opennlp/>

¹³ <http://nlp.stanford.edu/software/index.shtml>

- if the closest token to the one classified as V is tagged as a personal pronoun ('he', 'they', etc.) or existential there (i.e., 'there'), then S is an empty set
- if the closest token to the one classified as V is tagged as a pronoun (e.g., 'where', 'what' or 'who') then S={U.S. Air Force} where t is the closest token to the verb classified as a proper noun or noun
- if the two closest tokens to the one classified as V are tagged as a proper noun or noun and they are separated by a conjunction (i.e., 'and') then S={t}, with t being the closest token between the two

We also take into account negation; in particular, we associate the negation with the closest token classified as N, V, or A. We note that this extraction method can be problematic in the case of passive forms or in cases where there are co-references between different tokens in the sentences, known as anaphoric references. Most of the solutions proposed in the NLP community to solve these problems are related to the generation of a parse tree and the analysis of linguistic dependencies among tokens. In our case, we have found that these approaches increase computation time without delivering significant performance gains. In fact, in our case, the text is obtained from a machine translation stage and this can cause problems for parse tree generation. This is the reason for adopting an approach based on rules defined over the POS tags. Rules on POS tags, in our case proved to be more reliable than rules on parse tree structure built on the top of machine translated documents.

For example, in Table 5 we have sentences from the "Knowledge" cultural dimension, with its values "Maintenance" and "Change." In the same Table we also show some of the triples obtained from these sentences, we have bolded the subject and the object of the triples, and with "-" we indicate the missing element in the triple.

Table 5. Sample Sentences and Associated Triples for the 'Knowledge' Cultural Value Dimension

Knowledge	
Maintenance	Every Innovation is misguidance and every misguidance is in the fire.
Extracted Triples	(innovation ; be; misguidance), (misguidance ; be; fire)
Maintenance	America comes to change the fundamentals, of the nation changing the curriculum and blocking the road to awakening
Extracted Triples	(america ; come, change; fundamental, nation) (fundamental, nation ; change; curriculum) (curriculum ; block, road) (road ; awake; -)
Change	Religion becomes a dynamic and evolving concept addressing our problem and challenges.
Extracted Triples	(religion ; become; dynamic, evolving concept) (dynamic, evolving concept ; address, problem challenge)
Change	There are hundreds of Prophetic traditions that encourage Muslims to acquire all types of knowledge from any corner of the world.
Extracted Triples	(-, be, hundred prophetic, traditions) (hundred prophetic, traditions , encourage, Muslim) (Muslim ; acquire all, types knowledge corner world)

Step 3: Semantic Processing. In this step, we translate the triples obtained from the previous step into a set of triples comprised of concepts retrieved from a knowledge base. In particular, we use the lexical resource WordNet as a knowledge base (Fellbaum, 1998). In the literature, WordNet is a well-known resource that focuses on the semantic connections between words using linguistic criteria. As the most comprehensive semantic resource for the English language, we chose to adopt it in order to enrich the explicit semantic representation contained in the source material.

WordNet encodes concepts in terms of sets of synonyms (called synsets). WordNet (version 3.0) contains about 155,000 words organized into over 117,000 synsets. We associate a synset to each token using the function (ϕ) defined as follows:

$$\phi : t \rightarrow \operatorname{argmax}_{sy \in SY_t} \operatorname{score}(sy, C_t)$$

where t is the input token, SY_t the set of synsets associated to the token t in WordNet, C_t is S or V or O if t belongs to the subject, verb or object part of the triple respectively. The score is computed as follows:

$$\operatorname{Score}(S_y, C_t) = \sum_{s_y^* : \theta(s_y, R)} |C_t \cap \operatorname{gloss}(s_y^*)|$$

where $\operatorname{gloss}(s_y^*)$ is the set of words that is used to define the synset s_y^* in WordNet, $\theta(s_y, R)$ is a function that returns a set made up of s_y plus all the sets of synsets that can be obtained by s_y using the relations in (R) . This is one of the scores that has been used to cope with the word disambiguation problem (Navigli, 2009). It is based on the computation of the intersection between the context in which the word appears and the context in which the synset is defined. In our case, we compute the context of the synset using its gloss and the gloss of its semantic neighbors. By “semantic neighbors,” we mean the synsets obtained by applying different relations in Wordnet such as hyponymy, troponymy, hypernymy, meronymy, holonymy and entailment. We note that these relations are selected in line with the POS associated to the token. For example, we derived and expanded the synsets for “**concept**” that is classified as noun by looking at the closest synsets in WordNet that are also nouns.

After this automated processing step, our data has been reduced to sets triples whose constituent elements (i.e., subject, verb, and object) correspond to synsets in WordNet.

Step 4: Orientation. In this last step, we computed the orientation of each triple with respect to the cultural values. The orientation of a sentence s with respect to a dimension D is defined as follows:

$$O(s, D) = \frac{1}{|D|} \sum_{tr_j^* \in D} s_{tr}(tr_s, tr_j^*) - \frac{1}{|\bar{D}|} \sum_{tr_i^* \in \bar{D}} s_{tr}(tr_s, tr_i^*)$$

where tr_s is the set of triples extracted from s , D is the set of triples used as a reference for the cultural values set D and \bar{D} the set made by the triples that are not in D . The similarity s_{tr} between triples is defined as follows:

$$s_{tr}(tr_i, tr_j) = \frac{1}{|A| \cdot |B|} \sum_{sy_i \in A, sy_j \in B} s_{sy}(sy_i, sy_j) + \frac{1}{|V_i| \cdot |V_j|} \sum_{sy_k \in V_i, sy_r \in V_j} s_{sy}(sy_k, sy_r)$$

where A is the set of synsets derived from the union of S and O belonging to tr_i ; B is the set of synsets derived by the union of S and O belonging to tr_j ; and V_i and V_j are the set of synsets associated with the verb of tr_i and tr_j , respectively. The similarity function between two synsets S_{sy} has been previously validated in the computational linguistics literature (Leacock, Miller, & Chodorow, 1998). If we find a high similarity between two synsets and one of them is associated with a negation tag, then the similarity is defined as 0.

Analysis and Results

A total of 234 documents from the collection described previously were used in the analysis. Recall that most of the documents relate to religious sermons posted on religious sites or in blogs. In Table 6 we have the distribution of unique words used in the analysis collection. Documents in Arabic were first subjected to machine translation and then corrected by a native Arabic speaker, as described previously in Study 1.

Table 6. *Statistics of Word Distribution in our Corpus*

	Files	Total Words	Average Number of words for file
Arabic Documents	71	12406	637
English Document	163	222976	664

In order to deal with the uncertainty of the initial classifier used to discriminate relevant from irrelevant sentences, we additionally selected 150 sentences from a web site that provides free access to religious texts.¹⁴ In particular, we selected the sentences that have the highest jaccard coefficient with the ones collected in our dataset.¹⁵ These sentences served as background noise for the sentences that were analyzed. This step was taken because we need to evaluate our methodology in the presence of some noise, and the 150 sentences selected from the aforementioned website are sentences about religion that do not express any content related to cultural values.

For our experiment, we use half of our collection as a training set. This means that we use half sentences of our collections to derive a set of triples that are used in the computation of the orientation formula. In other words, the unseen triple is compared against half of our collection. We repeated this cross-validation process 10 times, by randomly dividing the collection in two parts. Figures 22-29 report the average results.

In those plots, the triples are on the X axis and the average orientation (sentiment) computed in the 10 experiments on the Y axis (range of orientation measure is [-1,1]). We observe that if we adopt a strict division into positive and negative values we reach reasonable levels of

¹⁴ <http://www.sacred-texts.com/download.htm9>

¹⁵ http://en.wikipedia.org/wiki/Jaccard_index

performance for several of the dimensions. Results for each of the four dimensions are described, in turn.

The orientations, or sentiment values, for the Coherence dimension were set so that homogeny had a positive orientation and diversity a negative orientation. As seen in Figures 22 and 23, the orientation values correspond reasonably well with the human annotation. If a cutoff for value classification is set at 0 (represented by +/- in the figures), then the average percentage agreement with the human raters is 79%, which is good in the context of automated sentiment analysis.

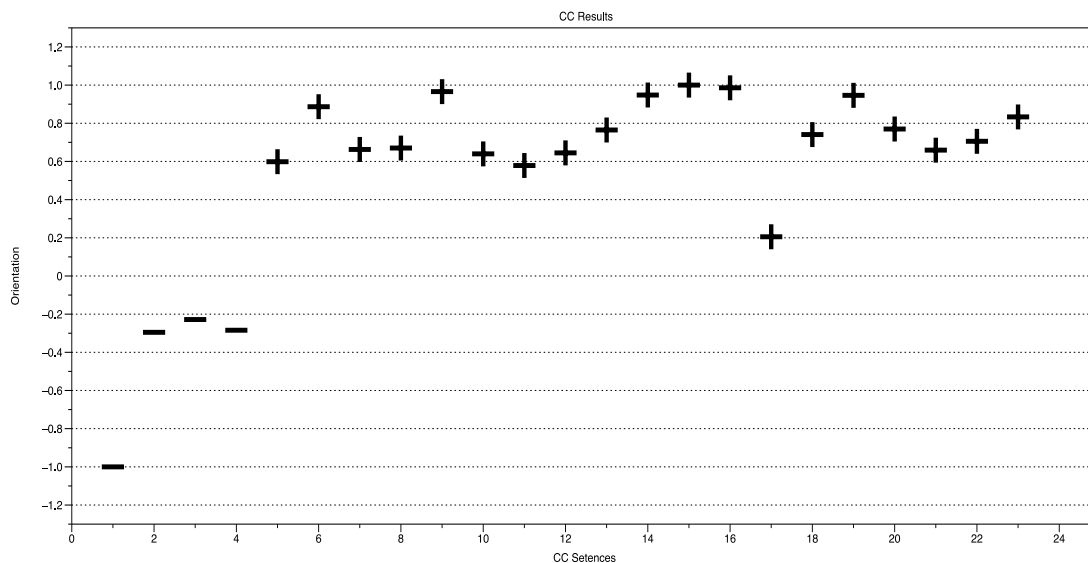


Figure 22. Coherence: Homogeny.

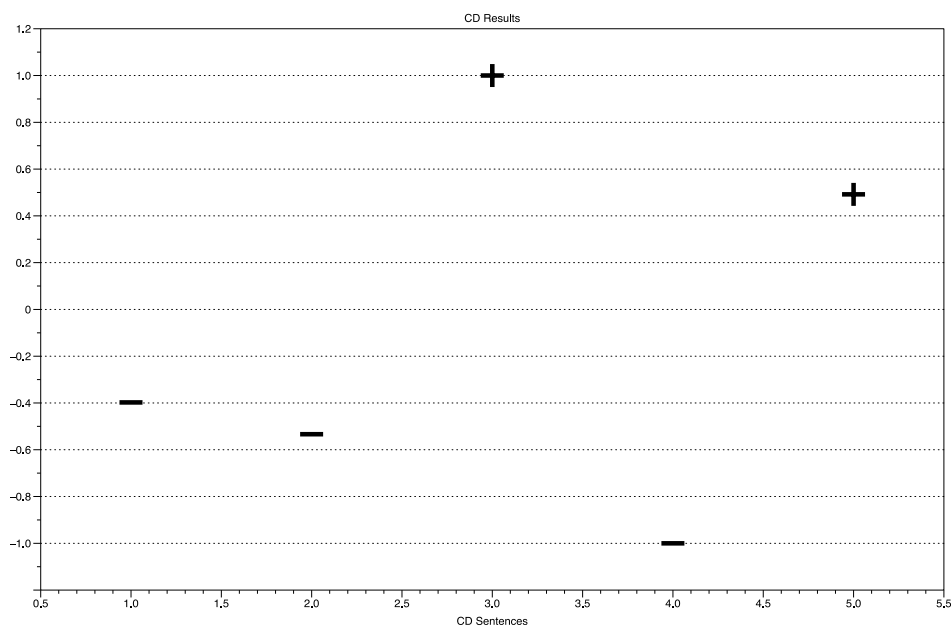


Figure 23. Coherence: Diversity.

The sentiment orientations for the knowledge dimension were set so that maintenance had a positive orientation and change had a negative orientation. As seen in Figures 24 and 25, the orientation values reveal a bias towards the change end of spectrum. Even so, the simple 0 threshold for value classification (represented by +/- in the figures) produces above chance reliability performance. If we correct for bias by setting the threshold to -.2, then the model achieves 67% average percentage agreement with human raters, which is reasonable performance.

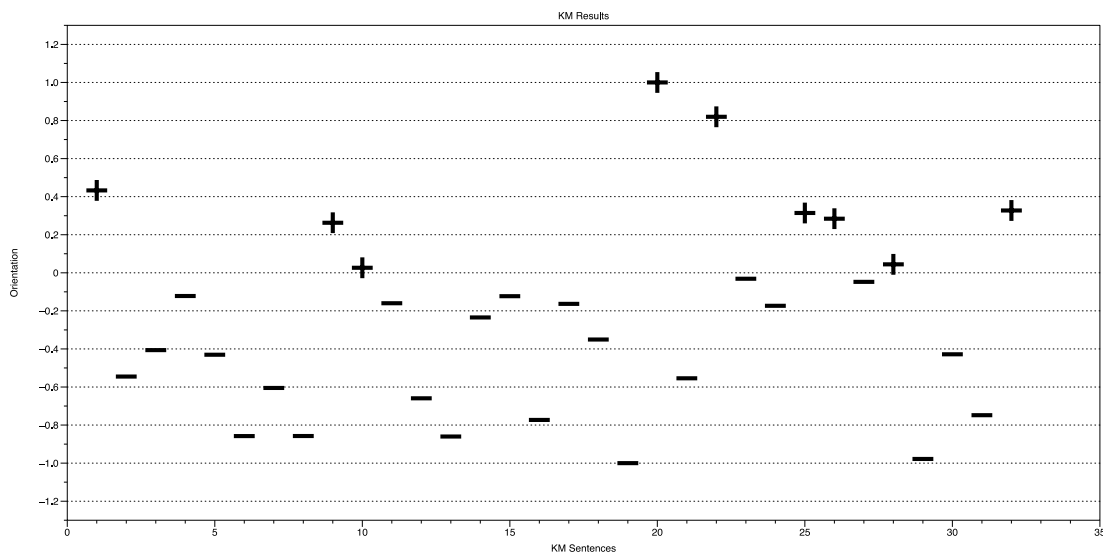


Figure 24. Knowledge maintenance.

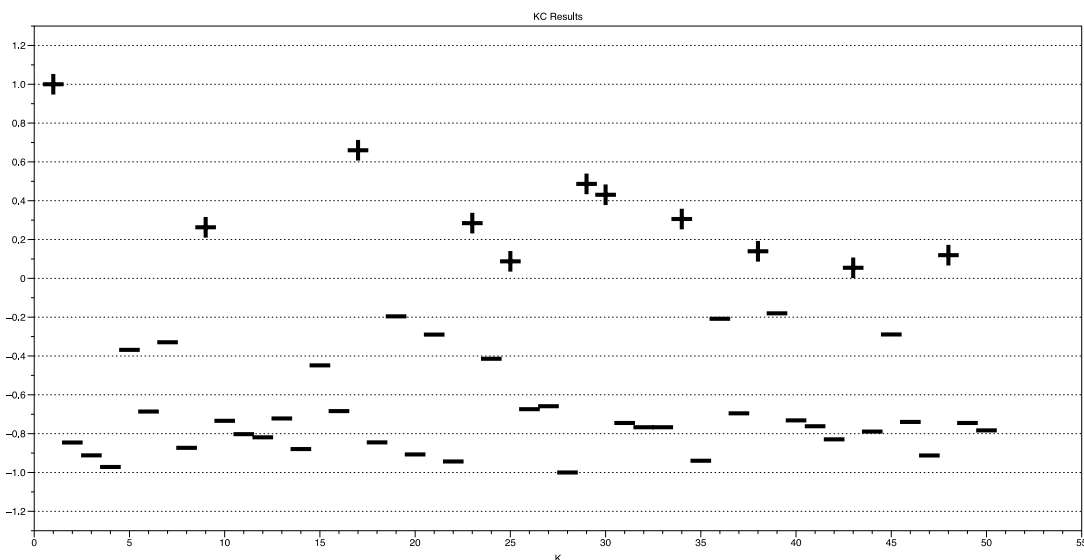


Figure 25. Knowledge change.

The sentiment orientations for the information exchange dimension were set so that separation had a positive orientation and interaction a negative orientation. As seen in Figures 26 and 27, the orientation values reveal a bias towards the separation end of spectrum. Even so, the

simple 0 threshold for value classification (represented by +/- in the figures) produces above chance reliability performance. If we correct for bias by setting the threshold to .4, then the model achieves 61% average percentage agreement with human raters, a moderate level of reliability for automated sentiment analysis.

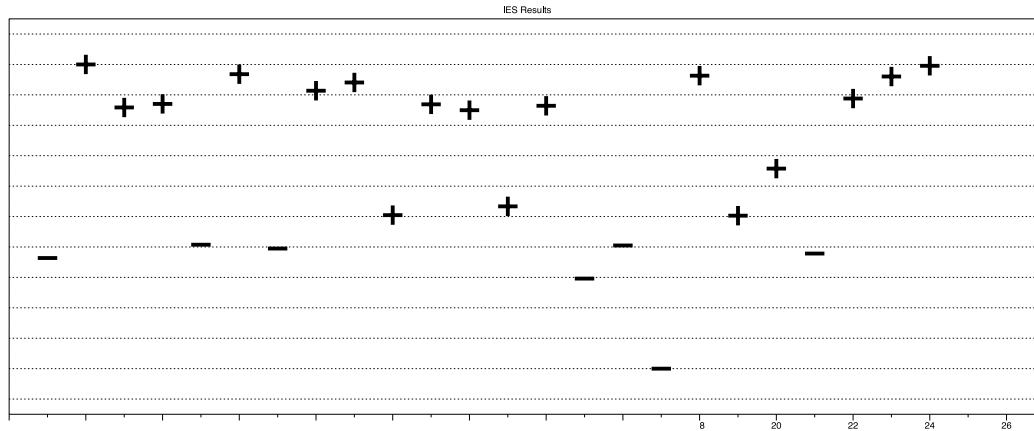


Figure 26. Information exchange: Separation.

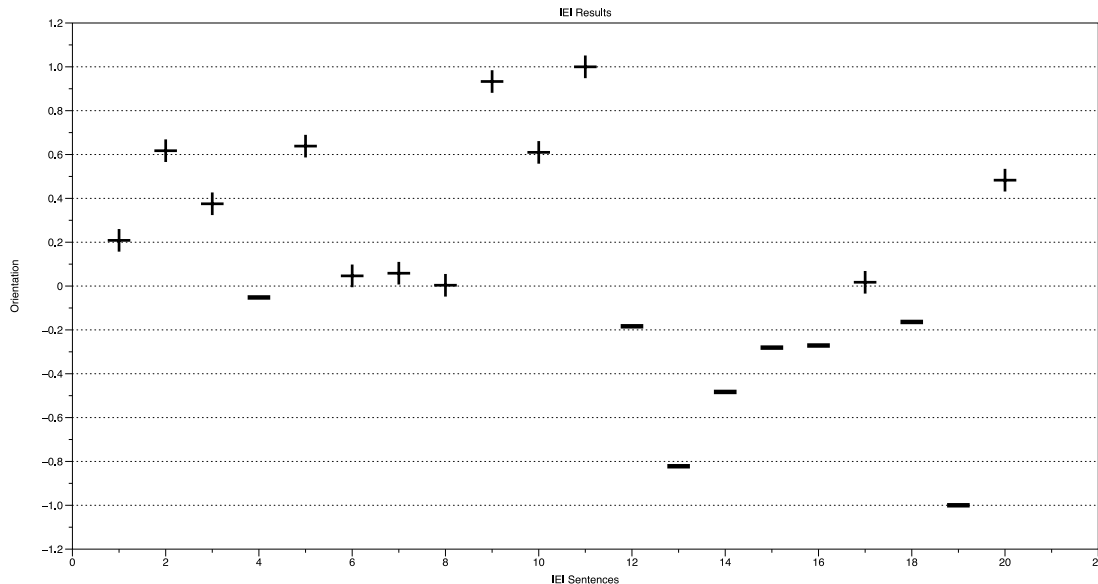


Figure 27. Information exchange: Interaction.

The sentiment orientations for the judgment dimension were set so that authority had a positive orientation and independence a negative orientation. Figures 28 and 29 illustrate similar levels of performance as the information exchange dimension, though without indication of bias. The 0 threshold for value classification (represented by +/- in the figures) achieves 60% average percentage agreement with human raters.

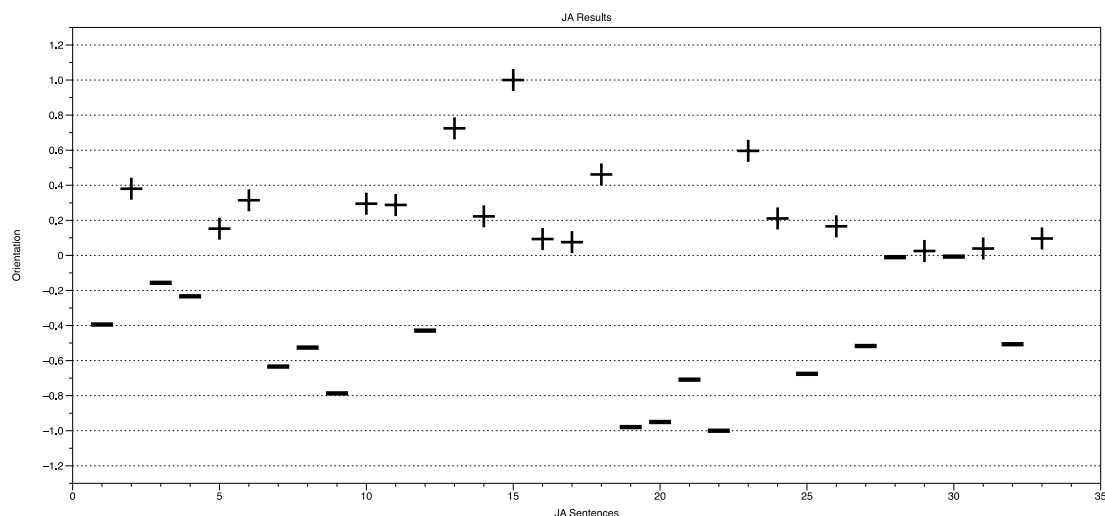


Figure 28. Judgment authority.

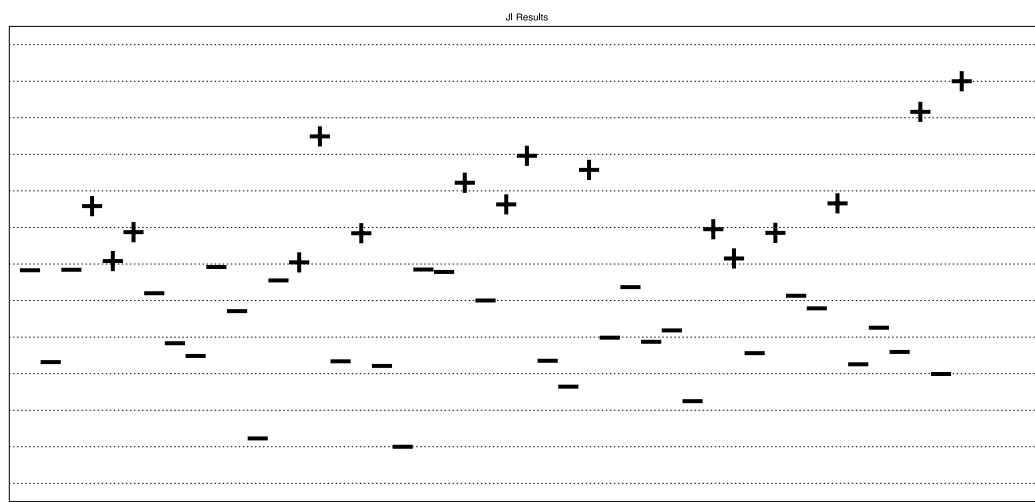


Figure 29. Judgment independence.

In sum, best sentiment classification performance was found for the Coherence and Knowledge dimensions, and the results for Information Sharing and Judgment dimensions were moderate. Most sentiment classification analyses have focused on very tangible objects for determination of attitudinal orientation (e.g., movies, food products, and the like). Until now, there has been little attempt to measure sentiments associated with intangible beliefs, such as the metacognitive beliefs explored here, and hence the presents results can be seen to set a new standard in the field. With respect to the substantive issue of measuring metacognitive values, the results correspond well with the findings of Study 1. These results provide additional confirmation for the conclusion that moderate and extremist ideologies can be discriminated on the basis of the metacognitive values that are embedded in their religious texts.

DISCUSSION

Methodological Implications

To the best of our knowledge, our approach is the first attempt to propose a computational method to measure extremist cultural values from web-based sources. However, previous research has addressed somewhat related issues. For example, an interesting survey of cultural influence in online-social question/answer behavior has been presented in the computer science literature, yet the study did not attempt computational methods to analyze their text data (Yang, Morris, Teevan, Adamic, & Ackerman, 2011). There have also been several recent additions to the literature on the extraction of sentiment information from Web-based sources (Lin, Xing, & Hauptmann, 2008). However, most of the techniques in the information extraction literature focus their attention on extraction algorithms and ignore the specification and selection of features that can support extraction goals. Most of the existing approaches are statistical based such as the one based on topic models (Blei, Ng, & Jordan, 2003). The topic model approach is based on the idea that a document can be represented as a mixture of topic distributions, a topic being a statistical distribution over the words belonging to the vocabulary of a considered corpus. Very few relevant applications exist, including a topic model to discriminate different ideologies in text (Lin et al., 2008), as well as proposed models to understand political ideals (Yano, Cohen, & Smith, 2009). In these cases, however, the goal was simply to distinguish between main political groups, as opposed to the current objective of measurement of degree of sentiment to particular ideals within groups. Ontological approaches, such as we have adopted here, have improved in their abilities with respect to more general text classification problems. For example, some research has been conducted on the improvements that may be obtained by using semantic features, and work to enrich the term vectors with concepts from the core ontology (Hotho, Staab, & Stumme, 2003). These researchers show how the procedure can improve the classification performance by solving the synonym problem and the identification of more general topics. In particular, they suggest three strategies where they choose to consider just concepts, terms, or combination of them. They show that with data sets like Reuters-21578, using a clustering algorithm like Bi-Section KMeans, they can have an improvement on the baseline of 8.4% by adding concepts to the terms vector and by using word sense disambiguation procedures and a hierarchy structure among concepts. An enhancement of the classical document representation through concepts extracted from background knowledge, and they use a boosting approach as classifier (Bloehdorn & Hotho, 2004). They show on Reuters-21578 collection a gain on the F1-Measure of 3.29%. In addition, some researchers have introduced the concepts of semantic kernels, their results indicate a consistent improvement on the F1-Measure values (Bloehdorn, Basili, Cammisa, & Moschitti, 2006; Wang & Domeniconi, 2008). The approach we have adopted naturally follows from these earlier efforts, extending the general ideas to cope with sentiments associated with abstract beliefs.

The current advances in automated sentiment analysis have been essential for applications to cultural modeling. Recent research in cultural modeling techniques has emphasized new ways of representing cultural knowledge (Sieck et al., 2010a). These representation formats have further led to novel developments in areas of semi-structured and structured elicitation methods for direct human data collection (Sieck et al., 2010c), as well as in simulating influences of information on culturally-shared beliefs (Sieck et al., 2011). A computational method for measuring cultural values in web-based resources adds another significant component to the

cultural analysts' toolkit. By providing a means to extract and quantify the cultural values embedded in large and increasing volumes of text being generated on the web, the present work moves a step closer to the realization of a "social radar" for monitoring and modeling changes in the sentiments of citizens and leaders (Maybury, 2010).

Substantive Implications

The successful exploitation of religious texts is often a key component of developing certainty among supporters of terrorist agendas. Yet, the specific kinds of religious ideas that promote such certitude lack systematic evaluation. That is, how do specific religious ideas eliminate doubt in the minds of religious extremists and their supporters? Our primary hypothesis is that extremist interpretations of religious doctrine include specific "metacognitive" beliefs that serve to erase doubt in the group's cause and provide psychological defenses against contrary views. Metacognitive beliefs are specific kinds of beliefs that affect the cognitive processes that govern feelings of confidence in worldviews. The excessive levels of confidence that ultimately result from certain types of metacognitive beliefs serve to promote decisive action. We expect that these kinds of beliefs are manifested in one form or another in the ideologies of any religious extremist organization, and possibly secular ones as well. In the current study, we examined Islam as a test case. Specifically, we compared various Muslim beliefs and doctrine as expressed on extremist and mainstream Islamic web sites. The findings of Studies 1 and 2 provide encouraging support for the metacognitive approach.

As described in the introduction, the overall goal of the present effort was to understand extremist ideological influences underlying terrorist and insurgent behavior, in a way that supports the future development of predictive models of adversary decision making. The *National Military Strategic Plan for the War on Terrorism* identifies extremist ideology as the enemy's strategic center of gravity, and DOD plays a significant role in establishing an environment unfavorable to extremist ideas, recruiting, and support (Wald, 2006). Yet, the specific ideological characteristics that serve as enablers for extreme action have not been well understood. The results of this project provide invaluable input to the development of accurate models of adversary decision making, as well as for the cognitive characterization of Islamic groups based on their ideological commitments in a way that directly supports information operations and strategic communications. A critical aspect of establishing an environment unfavorable to extremist ideas is to begin to take apart the rhetoric of terror sponsoring organizations, and address their ideologies through communication (Speckhard, 2006). In doing this, we may remove the appeal of religious-inspired myths of terrorist acts as the glorious correction of moral wrongdoing (Sageman, 2008). To make this approach work, we must first unpack the ideologies themselves, specifically, the extremist ideas that promote moral certainty within the terrorist mind. The current studies successfully demonstrate an approach, including both a model of cultural values embedded in such ideologies, and computational methods for extracting those values from web sources.

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APPENDIX A. JOURNAL OF TERRORISM RESEARCH PAPER

Sieck, W. R. (2011). A cultural models approach for investigating the cognitive basis of terrorism. *Journal of Terrorism Research*, **2**(1), 3-15.



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A Cultural Models Approach for Investigating the Cognitive Basis of Terrorism

by Winston R. Sieck

Principal Scientist, Culture and Cognition Group

Applied Research Associates

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Abstract

Terrorists attempt to communicate specific aspects of their ideological frameworks to shape the common perspective of their intended audiences. For the approach to be successful, the ideas they are promoting must fit within the cultural meaning systems shared across the population they are addressing. Knowing what messages will effectively persuade their constituents is likely intuitive for terrorists operating within their own cultural environment, but not necessarily for researchers who come from distinct cultural backgrounds. A method is thus described for studying in detail the common perspective that members of a culture bring to a situation. The method results in models of the culture that provide a basis for outsiders to begin to frame events from the cultural-insider point of view. The cultural models can then be used as an aid to anticipate how messages will be interpreted and evaluated by terrorists and their audiences.

Keywords: Cultural epidemiology, mental models, political violence, terrorist mind, jihad, Islam

The purpose of this paper is to describe an approach to cultural modelling, cultural network analysis (CNA), and its application to terrorism research. Cultural network analysis builds on a foundation of research practices drawn from the fields of cognitive anthropology, cultural and cognitive psychology, and decision analysis. It improves upon current cultural research techniques by providing a systematic method for constructing *cultural models* for groups, organisations, or wider societies. The essential idea is that, by studying in detail the common perspective that members of a culture bring to a situation, a model of the culture can be constructed that provides a basis for an outsider to begin to frame events from their point of view. The model can then be used for a variety of purposes, such as an aid to anticipating how messages will be interpreted and evaluated by members of the culture. Cultural models derived by CNA are represented graphically as a network of the culturally-shared concepts, causal beliefs, and values that influence key decisions in a particular context[1]. In their most fully developed form, cultural models also convey detailed quantitative information about the prevalence of their specific components. In order to establish a context for addressing



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contributions that cultural modelling can make to terrorism research, we briefly review progress made in understanding terrorism more generally.

Advances in understanding the reasons behind jihadist terrorism have been made in the last several years, though the evidential research base remains thin[2]. Generally, terrorist support and recruitment are not due to any single causal factor, but instead stem from the interplay between political aspirations of terrorist groups, vulnerable individuals, employment of jihadist ideology, and wider social support for terrorism. These latter components increasingly depend on a variety of modern modes of communication that are used to propagate the group vision of the world to a broad set of constituents. The overall communication strategies of jihadist terrorist organisations can be generally characterised as to:

1. motivate ordinary persons to carry out terrorist acts to meet the organisation's objectives;
2. exploit moral outrage and feelings of humiliation based on political events;
3. convince by means of religious texts used on behalf of terror ideology.

We discuss each of these components of terrorist strategy in turn. First, with respect to profiles of individuals, what research there is indicates that suicide terrorists have no appreciable psychopathology and are at least as educated and economically well-off as their surrounding populations[3]. Furthermore, education does not appear to be correlated with support for terrorism. Finally, although economic despair may provide a partial answer, it does not offer a complete explanation[4]. Importantly, individuals who are vulnerable to terrorist recruitment are not motivated to take part in suicide terrorism without some form of ideology to guide them, as well as an overall organisation to support their activities[5].

The balance of evidence suggests that terrorists tend to be from at least moderately religious backgrounds. For example, interviews with terrorist recruits in Pakistan indicated that, "None were uneducated, desperately poor, simple minded or depressed," and "all were deeply religious." They believed that their acts were "sanctioned by the divinely revealed religion of Islam"[6]. Furthermore, it also seems clear that religiosity is fostered as a part of the indoctrination process and those external events can trigger greater attention to religion. For example, Bosnian Muslims typically report not considering religious affiliation a significant part of identity until seemingly arbitrary violence forced awareness upon them[7]. This is not to suggest that the root of terrorist motive is religion, only that religious beliefs and values form an important component of jihadist groups' descriptions of their world.

The second component of jihadist terrorist strategy is exploitation of public emotional responses to political events. Terrorist organisations appear to be quite sophisticated in their use of modern



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media, including use of the World Wide Web to disseminate vivid imagery of moral wrongdoing by Americans and other agents of the West. Furthermore, humiliating and morally outrageous events are not considered isolated or random, but rather are interpreted within an overarching framework that a unified Western strategy exists to promote a “war against Islam”[8]

The third component of terrorist strategy is ensuring that recruits are so thoroughly convinced that they won’t consider backing out, let alone feel any mercy or remorse about their actions. For a suicide terrorist in particular, this means they will act with no doubt about their decision to die in order to kill others[9]. For example, the fully indoctrinated terrorist has been described as being completely free of any ambiguity or doubt about the mission or the means to accomplish it [10]. This religious conviction includes a fundamental belief that the terrorist knows the mind of God. Such a belief justifies a complete lack of tolerance for divergent ideas, even of other believers who disagree with the terrorist group on specific issues (i.e., the true believer exists apart from all others).

Each of these strategies relies heavily on terrorist communication of specific aspects from their ideological framework to shape the common perspective of their intended audiences. For the approach to be successful, the ideas they are promoting must fit within the cultural meaning systems shared across the population they are addressing. One application of cultural modelling to terrorism research is to explicitly map out the relevant cultural meaning systems in order to better understand how and why various messages appear to be effective in influencing people’s attitudes and garnering their support. Before addressing culture in terrorism, however, we first need to define *culture*.

Concept of Culture

There is a somewhat natural tendency to talk about culture as if it were a concrete, material thing. It is sometimes described as something people belong to, or as an external substance or force that surrounds its members and guides their behaviour. Although it is sometimes difficult to avoid speaking in these metaphorical terms, such an ethereal view does not provide a useful basis for a technical definition. An alternative approach begins by defining culture in terms of the widely shared ideas (such as concepts, values, and beliefs) that comprise a shared symbolic meaning system [11]. Within this conception, approximately equivalent and complementary learned meanings are maintained by a population, or by identifiable segments of a population. In this statement, ‘approximately equivalent’ acknowledges that no two people within a culture share exactly the same ideas, but rather highly-similar meanings are shared by most members of a society. The ‘complementary’ component refers to the fact that sharing of specialised knowledge depends on status and roles within a society (e.g. an imam and farmer).



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Taking this conception a step further, it is currently popular within cognitive science to draw on a disease metaphor for understanding cultural ideas, describing the ideas that spread widely through a population and persist for substantial periods of time as especially ‘contagious’[12]. This theoretical framework is often referred to as the epidemiological view of culture, drawing on the general sense of epidemiology as describing and explaining the distributions of any property within a population. The starting point for working from this epidemiological view is the individual idea as an atomic unit. People typically use the word *idea* to refer to any content of the mind, including conceptions of how things are and of how things should be. For instance, individuals may hold the concept that Western nations are joined together in a covert war against Islam. Their minds may also contain the value that imported Western ideals, such as the separation of religious and state affairs, are generally bad and so should be avoided. Ideas are often treated as independent units by social scientists, or grouped together into categories of belief for simplicity. A key premise of the current approach is that cultural knowledge consists of shared networks of ideas, and that there is value in explicitly considering clusters of ideas and their interrelationships. Networks of causally-interconnected ideas are often referred to as folk theories or *mental models* [13]. Such networks constitute people’s explanations for how things work, and result in judgments and decisions that influence their behaviour.

From this perspective *culture* refers to mental models, and other contents of the mind, for which there is some level of concordance across members of a population over a period of time. A potential issue associated with this definition of culture is how, then, to define the population of interest. The term *cultural group* refers to a population or sub-population of people that largely share the interconnected ideas of interest. The issue is that cultural groups are distinct from, but related to, demographic groups (i.e. groups based on nationality, educational status, etc.) in that the demographic delineations relevant to a particular cultural group will depend on how widespread the cultural ideas of interest are. For example, Sunni and Shia sectarian distinctions make little difference if the idea of interest is, “There is no god but Allah, and Mohammad is his prophet.” However, if the relevant common beliefs include those pertaining to the 13th Imam, then that demographic does become important. Hence, the relevant cultural group for a study will depend on the *cultural domain*, that is, the kind and topic of knowledge of interest.

Sunni Jihadist Cultural Model

Consider a Sunni Muslim extremist conception of socio-political relationships between Islam and the West. A mental model of such relationships contains an individual person’s concepts as well as their understanding of the causal relationships between concepts, i.e. the antecedents and consequences of political activities and their outcomes. This mental model influences the



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individual's expectations for how socio-political relationships will unfold and provides a framework for selecting behaviours and goals within this context. Figure 1 provides a network representation that might describe a Sunni Muslim's mental model of current political events. The set of ideas represented in Figure 1 were extracted from articles that describe jihadist narratives, and is presented here for illustrative purposes[14] [15] Figure 1 depicts a number of ideas using circles, lines, and colour. These ideas include simple concepts such as "Western arrogance" and "Muslim honour" represented as circles. It also includes causal ideas, such as that development of a new Islamic caliphate would decrease the extent of Western dominance and bring about a return of past Islamic glory. These are represented as lines in the figure, with +/- indicating the direction of the causal belief. Finally, Figure 1 portrays ideas of desired states or value using colour, as well as a logical flow across desired states. Developing an Islamic caliphate is a good thing. Maintaining (and enhancing) Muslim honour is likewise valued.

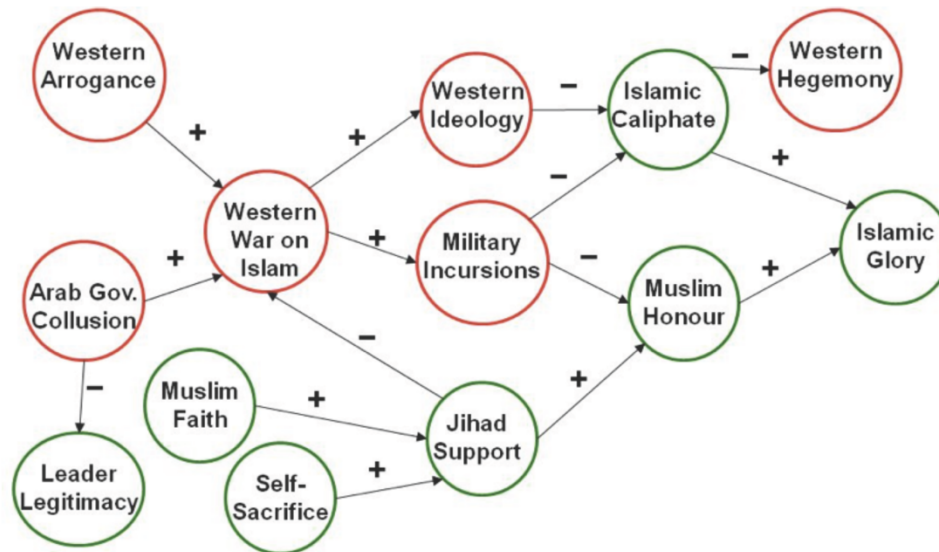


Figure 1. Sunni jihadist cultural model of political relationships



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According to the model, jihad is viewed positively and should be supported by the model's adherents due to the perceived anticipated consequences for Muslims. Most directly, support for jihad decreases the chances that the West will continue its war against Islam, and enhances collective Muslim honour. Holding the beliefs described by this mental model is likely to have fairly strong consequences for how a person will decide and act in a number of specific, relevant situations.

As implied by the name, mental models reside inside the heads of individuals. However, when people communicate with each other in any variety of modes, they develop mental models that may begin to resemble one another. Mental models can spread widely throughout a population, becoming 'cultural' in the sense of being shared by many of its members. A *cultural model* refers to an external representation of a set of culturally-shared mental models that is constructed by a researcher. A cultural model represents a consensus of the mental models for a particular cultural group and domain. Hence, for the Sunni Muslims who hold beliefs similar to the elements in this model, Figure 1 serves as one of their *cultural models* in the domain of socio-political relationships.

Considering Figure 1 as a cultural model gives us a precise way of identifying cultural transmission and cultural change [16]. For example, suppose the prospect of return to a glorious Islamic civilisation is the most salient perceived outcome that is positively influenced by the concept of supporting jihad. A change in the causal belief chain so that jihad in the present situation is seen instead as decreasing the chances of a glorious Islamic revival could affect a change in the value (or attitude) associated with acts that support jihad. That is, we might observe a change in the overall cultural model resulting from this shift in the specific causal chain of beliefs that link jihad to Islamic glory. Such an attitude change might then result in a re-examination and reinterpretation of Islamic texts, or at least the salience of such messages. This example highlights the interrelation between causal beliefs and values, in addition to illustrating how cultural models can represent cultural transmission.

Cultural Values, Models and Domains

Cultural psychologists have often conceptualised culture in terms of lists of domain-general, stable traits, such as individualist-collectivist value orientations [17]. Researchers operating within this programme aim to find a core set of dimensions for characterising cultures that they believe to be important across a wide variety of domains. The idea is to provide purely analytical predictions, a priori, about cultural groups that are widely applicable to many particular problems. For example, cultural researchers from this perspective might attempt to understand popular support for jihad in Middle Eastern countries by considering the general level



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of disparity of power held by members of those societies. An important assumption about culturally-shared mental models, in contrast, is that they are highly specific to particular domains [18]. That is, activities such as participation in a rally for Hezbollah are supported by mental models that are tailored to those specific activities. Hence the culturally-shared mental models comprise values, beliefs, and concepts that are salient to members of a particular culture in particular contexts, and may well not generalise to other situations. Multiple cultural values are reflected in people's mental models, and certain values may be more important than others depending upon the situation, a phenomenon sometimes known as *value trumping* [19]. For example, Americans typically place a high value on freedom of speech; however, they may also support censorship or restricted access to information at certain times (e.g., extremely violent or sexually-explicit content). Hence, from the cultural models perspective it is difficult to understand the cultural considerations that are relevant within a particular context by starting with pre-existing lists of "domain general" cultural values. This suggests that it is preferable to begin cultural analysis of a new domain in a more exploratory fashion, allowing values to emerge from the analysis along with their related cultural concepts and causal beliefs [20].

Mental models are naturally domain specific because they are explanations of the workings of particular artefacts and natural processes. Furthermore, mental models can vary across cultures in ways that are constrained only by the domain itself and any cognitive universals that ground shared understanding across humanity [21]. Most work on mental models has focused on the physical domain, though people also possess mental models that pertain to the psychological and social domains, as exemplified in Figure 1 [22]. A cultural model represents a consensus of mental models within the context of a particular domain.

One specific approach to cultural modelling begins by identifying the judgements or decisions of primary interest for study, such as a decision to engage in suicide terrorism. The decisions chosen arise in specific contexts as defined by critical incidents or scenarios. They are made by members of the cultural group being investigated, typically in a way that is surprising or confusing to members outside the group. Once the key decisions are identified, investigators build models of the cultural ideas that directly influence those decisions. This approach, called "cultural network analysis" ensures that the aspects of culture investigated are relevant to the decisions of interest.

Cultural Network Analysis

Cultural network analysis is a method for describing ideas that are shared by members of cultural groups, and relevant to decisions within a defined situation [23]. CNA discriminates between three kinds of ideas: concepts, values, and beliefs about causal relations. The cultural models resulting from CNA use network diagrams to show how all the ideas relate to one another. The



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CNA approach also includes the full set of techniques needed to build cultural model diagrams. This consists of specific methods to elicit the three kinds of ideas from people in interviews or survey instruments, extract the ideas from interview transcripts or other texts, analyse how common the ideas are between and within cultural groups, and align and assemble the common ideas into complete maps. CNA shares aspects with other approaches to cultural analysis, especially cognitive approaches developed by anthropologists [24]. However, it offers some specific aspects as a complete method that distinguishes it from other ways of examining cultures. These aspects include an emphasis on ensuring relevance of cultural models to key decisions to provide a more direct link to actual behaviour, portrayal of the cultural insider or 'emic' perspective, modelling interrelated networks of ideas rather than treating ideas as independent entities, and by seeking to directly estimate the actual prevalence of ideas in the network rather than relying on more vague notions of sharedness.

Cultural Network Analysis comprises an exploratory phase and a confirmatory phase. In the exploratory phase, concepts and mental models are extracted from qualitative sources, such as interviews and open source media (web news, blogs, email), with little presupposition regarding the elicited contents. One goal of this phase is to develop an initial understanding of the concepts and characteristics that are culturally relevant within the domain. A second objective is to obtain initial graphical representations of people's mental models in forms that closely match their own natural representational structure. Qualitative analysis and representation at this stage yield insights that can be captured in initial cultural models. Often, qualitative analysis may be all that is needed for applications. The exploratory phase also generates a wealth of material for constructing subsequent structured data collection in a confirmatory phase. In the confirmatory phase of CNA, structured interviews, field experiments, and automated semantic mining of web-based sources are used to obtain systematic data that is more amenable to statistical analysis. Statistical models used by cognitive anthropologists and market researchers are employed to assess the patterns of agreement and derive statistics describing the distribution of concepts, causal beliefs, and values. Finally, formal representations of the cultural models are constructed that illustrate the statistical and qualitative information in diagrams. Influence diagrams are an important representation format for cultural models, as illustrated in Figure 1. Formal representation makes it possible to use cultural models in a variety of applied contexts.

Cultural Models and Terrorist Cognition

Cultural modelling and the epidemiological view of culture can help to further understand the shared cognition of terrorists and their audiences. From the epidemiological view, culture is made up of contagious ideas, that is, ideas that propagate effectively within a population [25].



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Two broad objectives of research from this cultural epidemiology viewpoint are to characterise the current distribution of mental models within cultural groups, and to understand the dynamics of culture.

Fundamental cultural research programs from this perspective seek to address why some ideas are more infectious than others, and to explain the most widely distributed and long-lasting ideas within a population. Research for practical purposes has a slightly different focus. From a decision-making standpoint, for example, we recognise that many ideas may be pervasive but inconsequential to decisions of practical interest [26]. Hence, a decision-centred approach to culture and cognition begins with critical judgements and decisions that are made by members of a cultural group. For example, we conceive of the decision to accept the terrorist group's worldview as the central node within the highest-level of a hierarchy of terrorist cultural models. Using Cultural Network Analysis, we can study the networks of causally-interconnected ideas that are relevant to those decisions in order to answer a host of questions, such as:

1. What is the distribution of mental models shared among particular terrorist groups and their potential supporters?
2. How did the distribution get to be that way?
3. How stable are those distributions?
4. In what ways are the distributions changing over time?
5. How do individual ideas influence one another in these cultural belief networks?

Resulting cultural models and descriptions of their dynamics from such studies can provide considerable insight into the thinking behind communications that stem from terrorist groups. They also provide a basis for developing effective counter-communications by aiding in the determination of what makes for culturally meaningful messages. Cultural models would allow for making predictions concerning the effectiveness of a message by providing the opportunity to assess potential unintended inferences that individuals with a certain knowledge structure might make. Specifically, in a cultural models diagram, each concept and causal belief represents an opportunity to effect a change in beliefs or concepts. Hence, such diagrams can provide an orderly basis for determining the content of communications. Messages are created so as to affect the values of the most vulnerable concept nodes (i.e., those for which there is the least consensus) which then propagate across perceived influences to affect the values of other concepts. These effects spread through the cultural belief network, ultimately changing the value in overall perceptions or cognitions. With this CNA approach, information efforts focus on



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transmitting the most relevant information to effect conceptual change in a way that makes sense within the cultural group's understanding.

If the cultural group's understanding is mapped out in this way using their culturally relevant concepts and causal beliefs, then it can be relatively straightforward to identify critical concepts for targeting messages. Pursuing this strategy requires the following steps:

- create a cultural model relevant to the action or belief of interest;
- obtain relevant quantitative estimates of parameters in the model;
- simulate the cultural change effects of changes to detail-level concept values;
- identify the most vulnerable concepts and concept values as those for which the most disagreement exists;
- compose messages to affect the values of those concepts.

In sum, the results of CAN studies can provide valuable input to the development of accurate models of terrorist decision making, as well as for the cognitive characterisation of groups based on their ideological commitments. A critical aspect of establishing an environment unfavourable to extremist ideas is to begin to take apart the rhetoric of terror-sponsoring organisations, and address their ideologies through communication [27]. In doing this, we may find ways to remove the appeal of religious-inspired myths of terrorist acts as the glorious correction of moral wrongdoing [28].

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Author Biography

Winston R. Sieck, PhD, is a principal scientist at Applied Research Associates, where he leads the Culture and Cognition Group. He conducts fundamental and applied research on culture and decision making, including topics such as terrorist cognition, ideological conviction, intercultural understanding and cross-cultural communication. He received a PhD in Psychology with emphasis on cognition, culture, and decision making from the University of Michigan in 2000. Email: wsieck@ara.com

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APPENDIX B. ACM MEDES PAPER

Penta, A., Shadbolt, N. R., Smart, P. R., & Sieck, W. R. (2011, Nov.). Detection of cognitive features from web resources in support of cultural modeling and analysis. Paper presented at *ACM Management of Emergent Digital Ecosystems*, San Francisco, CA.

Detection of Cognitive Features from Web Resources in Support of Cultural Modeling and Analysis

Antonio Penta, Nigel Shadbolt, Paul Smart
School of Electronics and Computer Science
University of Southampton,
Southampton SO17 1BJ, UK
{ap7,nrs,ps02v}@ecs.soton.ac.uk

Winston R. Sieck
Applied Research Associates, Inc.
1750 Commerce Center Blvd
Fairborn, Ohio, 45324, USA
wsieck@ara.com

ABSTRACT

The World Wide Web serves as a valuable source of culture-relevant information, which can be used to support cultural modeling and analysis activities. Part of the challenge in exploiting the Web as a source of culture-relevant information relates to the need to detect and extract information about beliefs, attitudes, and values from a variety of different resources. The Web, thus, features a rich variety of information resources, and these are seldom categorized with respect to the dimensions in which cultural analysts are interested. Exploiting the Web as a source of culture-relevant information therefore requires techniques and approaches that enable cultural analysts to extract relevant information and organize extracted content in various ways. In this paper, we outline an approach to assist cultural analysts in the extraction and organization of relevant information. We show techniques that can be used to extract information of the attitudes, beliefs, and values of individuals, and how this data can, in turn, be used to support cultural modeling and analysis.

Categories and Subject Descriptors

H [Information Systems]: *Social Computing, Cultural Modeling, Cognitive Features Detection*; H.3 [Information Search and Retrieval]

1. INTRODUCTION

The World Wide Web (WWW) serves as a valuable source of culture-relevant information, which can be used to support a number of cultural modeling and analysis activities. A number of factors, however, militate against the widespread use of the Web in cultural analysis contexts. One difficulty relates to the fact that Web content is seldom represented and organized in ways that support cultural modeling and analysis. If cultural analysts therefore wish to test specific hypotheses regarding the distribution of beliefs, values and attitudes (what we collectively refer to as “*Cognitive Features*”) among different groups, they are often prevented

from doing so in a Web context because the data is simply not available in the right format. Typically, culture-relevant information is embedded in resources containing other kinds of content, and this makes systematic forms of data analysis highly problematic. Ideally, what is required are representational schemes that enable cultural analysts to flexibly manipulate data in ways that support hypothesis testing and theory development. A second, not altogether unrelated concern, associated with the use of the Web as a source of culture-relevant information relates to the fact that relevant data is often not explicitly represented in the target resources. For example, if we are looking for evidence of particular Cognitive Features in natural language resources, then we will often have to analyze the meaning of the source text; seldom will target Cognitive Features be represented in such a way that they can be easily detected by automated processing techniques. In light of these difficulties, it is important to develop a range of information extraction, representation and manipulation capabilities. Such capabilities need to be flexible enough to extract a range of Cognitive Features, and they need to be sensitive enough to detect those features even when the target features are “hidden” in natural language texts (a problem that is akin to the detection of weak signals in a lot of background noise). Finally, information manipulation capabilities are required to support hypothesis testing and cultural modeling activities. The development of these capabilities will support the use of the Web as a resource for cultural analysis and cultural model development. In this context, the aims of the paper are: i) to propose a general framework that can be used to support the detection, extraction and representation of Cognitive Features; ii) to show how we can use statistical techniques to implement the proposed framework; iii) to show in a preliminary case study how the Cognitive Features can be useful patterns to detect members belonging to an extreme religious domain. To the best of our knowledge, ours is the first attempt to propose a computational approach to address the cognitive models by a cultural framework. An interesting survey of cultural influence in social behaviour is presented in [9]. Obviously, there is a rich literature concerning the extraction of particular bodies of information from Web-based sources [1]; however, most of the techniques that are described in the information extraction literature focus their attention on extraction algorithms while ignoring the specification and selection of features that can be used to support extraction goals. In this paper, we use an approach that is based on the notion of Topic Models. Blei et al [2] first used this approach to represent a document as a mixture

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of topic distributions, a topic being a statistical distribution over the words belonging to the vocabulary of a considered corpus. A number of variants of this approach have been proposed in the literature; for example [6]. In the current paper, we adopt the notion of Topic Models, but we extend the notion to include a new graphical model component, and we also give a specific meaning to the distributions used in our models (this is something that is rarely discussed in the context of Topic Model research).

The current paper is organized as follows: in Sections 2 and 3 we provide an overview of our approach to Web-based knowledge extraction in support of cultural modeling and analysis; in Sections 4, 5, and 6 we present the methodology used to represent the analytic substrate of the information extraction process for the Web-based textual sources; in Section 7 we describe the technical approach used to analyze the text sources; and in Section 8 we present a specific example of our approach focused on the domain of religious extremism.

2. CULTURAL ANALYSIS AND COGNITIVE FEATURES

We adopt an epidemiological approach to culture, which sees inter-individual similarities in cognition as the basis for cultural groupings [8]. A fundamental assumption of this perspective is that shared developmental experiences lead to important similarities in the mental representations (e.g. concepts, beliefs and values) that are distributed among members of a population. The Web appears as the right place to study how ideas are spread among behavioral norms, discussions, interpretations, and affective reactions within specific populations. We are interested in models that are able to elicit, analyse, and represent the beliefs, values, and cognitive concepts that are shared by members of a cultural group and how these affect their decisions or how they are connected. First, let us give an informal definition of what is, for us, a cultural group:

DEFINITION 1. A Cultural Group is a collection of people who are grouped together by virtue of their similarity along specific cognitive dimensions; e.g. commonality of beliefs, attitudes and values.

Now let us describe how we model the relationship among a cultural group and the cognitive signatures of its individuals in our perspective. We start from the modelling approach that was developed in [8]. The approach is called Cultural Network Analysis (CNA). In CNA, a conceptual model based on belief network is used to show the cultural knowledge within a population. We model the Cognitive Features as follow:

DEFINITION 2. A Cognitive Feature (CF) is one of the following structures: 1) a triple $\langle B, v, \delta \rangle$, with B being a belief, v one of the values of B and $\delta \in \mathbb{R} \cap [-1, +1]$ a measure of the value or belief perception in a group or individual: negative ($-1 \leq \delta < 0$), positive ($0 < \delta \leq 1$) or neutral ($\delta = 0$); ii) a triple $\langle C, E, p \rangle$, with C and E being cause and effect, respectively, of the casual relationship $C \rightarrow E$ and $p \in \{+, -\}$ is a negative ($-$) or positive ($+$) polarity.

According to our epidemiological approach we simply define our model as follows:

DEFINITION 3. A Cultural Model (\mathcal{M}) is a set of Cognitive Features

For example, to understand what is meant by the terms “belief” and “value”, let us consider the religious domain. In this domain, we introduce some beliefs known as *meta-cognitive beliefs*. The terms *meta-cognition* refers to the beliefs about how one thinks and learns [7]. In particular, these beliefs are the ones that affect the cognitive processes that govern feelings of confidence in world-views. In Table 1 are reported the meta-cognitive beliefs that we introduce together with their values. We reported just an example of the meaning of these beliefs such as the one related to the belief *Knowledge*. Knowledge belief has two values: i) *Maintenance* that represents ideas that emphasize the priority and continuance of long-established conceptions of the world used to block new information, interpretations; ii) *Change* that represents a belief that emphasises knowledge acquisition and change at the individual and cultural levels and it implies that existing beliefs may be wrong and incomplete, or no longer fit with current situations. Further explanation of those metacognitive beliefs can be found in [7]. Examples of causal relationship in a cultural environment can be the triple $\langle \text{Religion}, \text{Innovation}, - \rangle$. This means that we can have a decrease in the Innovation proportional to a rise of a Religion. For example, if we process the infor-

Meta-Cognitive Beliefs		
	Knowledge	Coherence
Values	Maintenance (KM)	Homogeny (CH)
	Change (KC)	Diversity (CD)
	Information Exchange	Judgement
Values	Separation (IES)	Authority (JA).
	Interaction (IEI)	Independence (JI)

Table 1: The meta-cognitive beliefs and their values used to categorized the cultural signals in the religious domain.

mation coming from two kind of cultural groups characterized by an extremist (G_E) or moderate (G_M) vision about the meaning of the religion in the world, we can imagine to obtain the following cultural models $\mathcal{M}_E = \{ \langle \text{Knowledge}, \text{maintenance}, 0.9 \rangle, \langle \text{Judgement}, \text{authority}, 1 \rangle, \langle \text{Religion}, \text{Innovation}, - \rangle, \langle \text{War}, \text{Honour}, + \rangle \}$ for G_E . $\mathcal{M}_M = \{ \langle \text{Knowledge}, \text{change}, 1 \rangle, \langle \text{Coherence}, \text{Diversity}, 0.6 \rangle, \langle \text{Thinking}, \text{Freedom}, + \rangle, \langle \text{Democracy}, \text{Religion}, + \rangle \}$ for G_M . s, without taking into account the idea of their positive, negative or neutral attitude.

3. COGNITIVE FEATURE DETECTION

One way in which Cognitive Features are manifested on the Web is in response to the occurrence of particular events, for example, military interventions, terrorist attacks, public protests and so on. These events elicit responses that reveal something about the beliefs, attitudes and values of the respondents to the event in question, and they therefore reveal something about respondent cognitions. Given the aforementioned cognitive characterization of culture, we can see that individuals' responses to particular events can be a valuable source of cultural information. This is one reason

why the Web serves as a source of culture information. The advent of Web 2.0 has supported greater participatory interaction with the Web, and enabled individuals to contribute to Web content. If information extraction technologies can be used to extract information about individual cognitions from the kind of resources in which individuals typically express their views (for example, blogs, twitter feeds, discussion forums, and so on), then we may be able to detect some of the features that are important for cultural analysis and modeling. In order to support this detection process, we are interested to process sources that deliver signals that we define as *cognitive*. Let us first introduce informally what we mean for cognitive signals as follows:

DEFINITION 4. *The Cognitive Signals are all the messages where the people elicit their thinking referable to a cultural knowledge within a population. These messages have to be automatically processed and can be exchanged using different media.*

Examples of sources, that convey Cognitive Signals and how these can be used to detect the relationships between the individuals and a cultural group, are presented in Figure 1. For example, an image can be an important indicator of the relationships between Web page authors and the cultural groups to which they belong. In particular, a more complex analysis is required based, for example, on how much these signs are used among linked members or for example in which position they are depicted. Intuitively, an image on the title banner is more valuable than others. Example of images are: i) logos related to political organizations (Figures 1.a, 1.b); ii) flags (Figures 1.c, or of a 1.d); iii) symbols of terrorist groups (Figures 1.a,1.b); vi) images of historical characters (Figure 1.h). Another example, in this case in video format, is represented in Figure 1.g. It is the famous speech about freedom in the Braveheart movie. A high degree of content sharing among a community provides an indication of how important notions such as freedom are among a group and how they think about freedom. Most of these signals can not be processed separately, so a multi-modal analysis using different media is required. Processing different signals over different media channels can provide important inputs to cultural modeling and analysis. In spite of the importance of multi-modal analysis, much of the input for Cognitive Feature detection will probably come from text-based sources. In this paper, we focus our attention on the Cognitive Features extracted from signals related to text sources. Examples of text sources that are relevant from the cultural point of view are depicted in Figure 1.i and Figure 1.l. These sentences reveal the views of content authors that reflect their membership of particular cultural groups (for example, moderate or extremist religious groups). In this setting, the Cognitive Features detection process aims to model, extract, and process those Cognitive Signals in order to detect the Cognitive Features and eventually structure all the results of this process in what we call *Cognitive Patterns*. Let us give a formal definition of this object.

DEFINITION 5. *Let us consider a Cultural Model \mathcal{M} and one of its Cognitive Feature τ . A Cognitive Pattern ($\mathcal{P}_{\mathcal{M}}^{\tau}$) associated to τ belonging to \mathcal{M} is a set of triples as $\langle r, \tau, \mu \rangle$, where r a source containing a Cognitive Signals referable to an individual or group within a population and $\mu \in [0, 1] \cap \mathbb{R}$ a measure of how r is reliable to be a representative of τ on the considered individual, group or population.*



Figure 1: Examples of Cognitive Signals in different media formats.

We note that in this setting the resource r can be any data belonging to a group in any format that an expert identifies as a valuable source of cultural information. Then, this detection process has the aim to populate a “Cultural Pattern Database” (\mathcal{Pdb}) where all this knowledge is stored and updated by domain experts. Now, let us describe how we deal with the Cognitive Signals related to the text sources.

4. THE TEXT WEB SOURCES

In this section we explain how we model and extract signals from the text related to a web page. First we give a more formal definition of how we model the text messages and then how we extract our model from a text document.

4.1 Text Signal Modeling

We model the text using a linguistic model known as the N-gram approach [5]. In this model, the text is divided into structures, known as *gram elements*, which are formed by tokens extracted from the text. Let us consider a text fragment and assume that we extract from it some gram elements, looking at the words as linguistic tokens. Firstly, we use the term *gram elements types* to indicate the type of ngram extracted. A gram element type can be associated to one of the following *category*: uni-gram, bi-gram or tri-gram. Let us introduce the definition of *Text Signal* as follows:

DEFINITION 6. *A Text Signal is a set of gram elements belonging to the same category. In particular, we use the following symbols: i) \mathcal{T} for the Text Signal made by uni-gram; ii) \mathcal{T}^2 for the Text Signal made by bi-gram; iii) \mathcal{T}^3 for the Text Signal made by tri-gram.*

Now, looking at the Part of Speech (PoS) tag [5] associated with each word belonging to a Text Signal, we can differentiate them as follows:

DEFINITION 7. *Let us consider the following elements $(w_i) \in \mathcal{T}$, $(w_i, w_j) \in \mathcal{T}^2$, $(w_i, w_k, w_j) \in \mathcal{T}^3$, and let us attach to all of them their Part of Speech (PoS) labels as follows: : (w_i/l_i^1) , $(w_i/l_i^2, w_j/l_j^2)$ and $(w_i/l_i^3, w_k/l_k^3, w_j/l_j^3)$. We can differentiate these Text Signals using the computed PoS labels as follows:*

- *A Text Entity Signal is a subset of those elements belonging to \mathcal{T} or \mathcal{T}^2 or \mathcal{T}^3 that fulfil the following conditions: i) for \mathcal{T} , l_i^1 is a noun or proper noun; ii) for \mathcal{T}^2 , we have that both l_i^2 and l_j^2 are nouns or proper*

nouns; iii) for T^3 , we have that both l_i^3, l_j^3 are nouns or proper nouns and l_k^3 is a verb. We use the following symbols $\mathcal{E} \subseteq T$, $\mathcal{E}^2 \subseteq T^2$, $\mathcal{E}^3 \subseteq T^3$ to refer to those subsets.

- A Text Sentiment Signal is a subset of those elements belonging to T^2 or T^3 that fulfil the following conditions: i) for T^2 , we have that l_i^2 is a noun or proper noun and l_j^2 is an adjective; ii) for T^3 , we have or l_i^3 is a noun or proper noun, l_k^3 is a verb and l_j^3 is an adjective, or l_i^3 is a noun or proper noun, l_j^3 is an adjective and l_k^3 is adverb, or l_i^3 is a noun or proper noun and both l_j^3 and l_k^3 are adjectives. We use the following symbols $\mathcal{S} \subseteq T$, $\mathcal{S}^2 \subseteq T^2$, $\mathcal{S}^3 \subseteq T^3$ to refer to those subsets.

For example, using the sentence in Figure 1.i a Text Entity Signal can be {*religion*, *history*, (*religion*, *interpretation*), (*religion*, *root*, *history*)} and a Text Sentiment Signal can be {(*religion*, *dynamic*), (*religion*, *become*, *dynamic*)}.

4.2 Text Signal Extraction

We can now describe the process to extract Text Signals from an unstructured text document d . We first pre-process d by sending it to a standard Natural Language Processing (NLP) pipeline made up of the following components: Sentence Tokenizer, Word Tokenizer, Part of Speech tagger, Stop Word Eliminator, etc. (more details about these NLP steps can be found in [5]).¹ After these phases, we represent each of the sentences of d as a vector of words with a related vector corresponding to the PoS annotation of each word. For example, for the sentence s_i in d , we have a vector \vec{x}_i made by the words plus an associated vector \vec{x}_{Li} of the same cardinality of \vec{x}_i such that $\vec{x}_{Li}[k] = l_k$ is the PoS label of the word $w_k = \vec{x}_i[k]$. The elements of \vec{x}_i are the words filtered in the previous NLP pipeline. Then, we can derive, for each vector, a Text Signal. In the case of T , we have just the elements of a vector \vec{x} , instead for T^2 and T^3 we reduce the possible number of binary and ternary combinations of elements belonging to a vector, by choosing a maximum linguistic dependency that have to be considered among its words. In particular for T^2 and T^3 the strategy used to extract bi-grams and tri-grams from a vector is depicted in Figure 2. In particular, we choose a *dependency window* w and then from this value we can compute the indexes used to extract the bi-grams and tri-grams. In Figure 2, the indexes for a generic step i of our extraction process are depicted both for bi-grams and tri-grams. Note that in Figure 2 we choose the same dependency window w for both bi-grams and trigrams. In general, if we have a vector of cardinality N , we extract: i) $(N - w_b)w_b + \frac{w_b(w_b - 1)}{2} \ll \binom{N}{2}$ number of bi-grams if $N > w_b$ being w_b the dependency window for a bi-gram, otherwise all the different combinations; ii) $(N - 2w_t)w_t^2 + w_t^2(w_t - 1) \ll \binom{N}{3}$ number of tri-grams if $N > 2w_t$ being w_t the dependency window for a tri-gram, otherwise all the different combinations. After computing T , T^2 , T^3 using a vector \vec{x} , we can apply a filter based on the information computed in \vec{x}_{Li} , in order to obtain the

¹If there is a "not" that comes before an adjective, we collapse the negation with the adjective to create unique words, for example "not good" becomes "not-good". This is important in order to deal with the negation of an adjective, which can completely change the meaning of the adjective itself

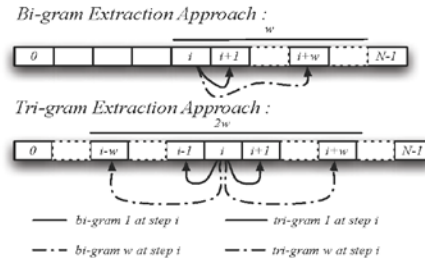


Figure 2: Approach to the extraction of bi-gram and tri-gram from a vector of words.

Text Entity Signal and Text Sentiment Signal as described in Definition 7.

5. COGNITIVE ANNOTATION

The problem now is to understand how we can use the previous text signals in order to detect our Cognitive Features. We use a supervised approach, where the cultural analysts give an initial subset of annotated resources that are used by the methods described in the next sections. We call this initial set the *Cognitive Annotations*. For example a cultural expert can initially select from the Web a text fragment, such as the one belonging to a blog, because this is valuable to describe the Cognitive Features τ_j within the Cultural Model \mathcal{M}_i . This annotation can be initially given by the analyst in a way similar to how we describe the Cognitive Patterns. For example using the Cultural Model defined previously \mathcal{M}_E and \mathcal{M}_M , their annotation can be structured as follows: $\mathcal{P}_{\mathcal{M}_E} = \{ \langle \text{"religion is distorted"}, \langle \text{Knowledge, maintenance, 0.3} \rangle, 1 \rangle \}$; $\mathcal{P}_{\mathcal{M}_M} = \{ \langle \text{"knowledge is the first step in firm belief and conviction"}, \langle \text{Knowledge, change, 0.8} \rangle, 0.6 \rangle \}$. We consider a real scenario in which the resources are unstructured texts and the cultural analysts can be different so we need to define how we process these annotations in order to build particular valuable patterns that are related with these annotations. Let us describe how we process a text annotation tf_k that a cultural analyst made for the Cognitive Features τ_j belonging to a Cultural Model \mathcal{M}_i and how we define these Cognitive Annotations. In particular we suppose that each text-based resource used in the annotation is a sentence. We process this unstructured knowledge to extract the Entity and Sentiment Text Signals in the same way described in Section 4 for the Text Signals, using the NLP pipe, the bi-grams/tri-gram extraction process and the PoS filter. After this process, we have the following sets T , T^2 and T^3 or \mathcal{E} , \mathcal{E}^2 , \mathcal{E}^3 , \mathcal{S}^2 and \mathcal{S}^3 . Now we build a Cognitive Annotation as a special Cognitive Pattern $\mathcal{P}_{\mathcal{M}_i}^{\tau_j}$, where a triple is $\langle \mathcal{A}_i^k, \tau_j, \mu_i^k \rangle$. Being \mathcal{A}_i^k a set of gram elements computed over the initial resources tf_k and μ_i^k a new reliable measure. In particular we divide these annotations into i) *Simple Text Cognitive Annotation* if \mathcal{A}_i^k is one of the following sets: T , T^2 , T^3 ; ii) *Entity Text Cognitive Annotation* if \mathcal{A}_i^k is one of the following sets: \mathcal{E} , \mathcal{E}^2 , \mathcal{E}^3 ; iii) *Sentiment Text Cognitive Annotation* if \mathcal{A}_i^k is one of the following sets: \mathcal{S}^2 , \mathcal{S}^3 . Let us now explain how we compute the new reliable

measure μ_i^k . In order to compute this new measure we use the previous annotations. The value μ_i^k in $\langle A_i^k, \tau_j, \mu_i^k \rangle$ can be computed as follows:

$$\mu_i^k = \alpha_1(\text{avg}(NMI_{A_i^k})) + \alpha_2(\mu_k) \quad (1)$$

In this equation, we use a convex combination, $\alpha_1 + \alpha_2 = 1$, of the average (*avg*) value of the Normalized Mutual Information [5] computed for each gram element in A_i^k , i.e. $NMI_{A_i^k}$. With μ_k we mean the initial value associated by a domain expert to annotate the resource tf_k . We compute the Normalized Mutual Information as follows: we indicate with g a gram element belonging to A_i^k and with τ_j the related Cognitive Features. We define for g and τ_j two binary random variables X_g and Y_{τ_j} respectively and then we compute an associated contingency table, such as the one depicted in Figure 3. In this table, we represent the frequencies related to how much a gram g is used to describe τ_j or not.² In particular, the sub-references of 0 and 1 used in the table in Figure 3 are used to indicate the absence or presence of our variables. For example, if we would measure the events

		Cultural Element (τ_j)		
		0	1	
gram element (g)	0	N_{00}	N_{01}	N_{g0}
	1	N_{10}	N_{11}	N_{g1}
		$N_{\tau_j 0}$	$N_{\tau_j 1}$	

Figure 3: Contingency Table used to compute the Normalized Mutual Information.

in which the considered gram element is used to describe τ_j , the joint probability is $P(X_g = 1, Y_{\tau_j} = 1) = \frac{N_{11}}{N_{tot}}$, being N_{11} , the number of times the gram element g is used in the resources associated with the Cognitive Features τ_j and N_{tot} the total number of gram elements of the same gram element type of g stored in all the annotations. Then, we compute the Normalized Mutual Information for g and τ_j as follows:

$$NMI(X_g, Y_{\tau_j}) = \frac{MI(X_g, Y_{\tau_j})}{\min(H(X_g), H(Y_{\tau_j}))} \quad (2)$$

$$MI(X_g, Y_{\tau_j}) = \sum_{r \in \{0,1\}} \sum_{t \in \{0,1\}} P_{12} \log\left(\frac{P_{12}}{P_1 P_2}\right)$$

where $H(*)$ is the entropy of a random variable $\{*\}$, $P_{12} = P(X_g=r, Y_{\tau_j}=t)$, $P_1 = P(X_g=r)$ and $P_2 = P(Y_{\tau_j}=t)$ and MI the Mutual Information. We note that this procedure is useful to understand what are the best annotations that can be used within our process. This procedure can also be triggered every time we have a new annotation in order to use the best knowledge collected by the domain expert. We call "Cognitive Annotation Database" (*C.Adb*) the place where all this knowledge is stored and updated by domain experts.

6. THE GRAM ELEMENTS DISTANCES

In this section, we explain how we compare the gram elements, such as the ones belonging to the sets introduced in

²We consider each belief against the rest as in a leave-one-out approach.

the above sections. Computing semantic distances among the words in the extracted gram elements can require a lot of time due the complexity of the measures related to the navigation of the knowledge used to support this computation. In order to optimize this step, we used a hybrid approach based on a linguistic and semantic distance. This approach has the aim to choose a different distance computation according to the PoS labels associated with each word of our gram elements. We define the following strategies:

- *Strategy 1 (S1)* based on the *Edit similarity* that measures how many linguist operations we need to use in order to transform one word into another one.
- *Strategy 2 (S2)* based on the *Jaccard similarity* that measures how many elements two sets have in common. In particular, for each word we build a set with the synsets retrieved from the WordNet [4] database that are connected at maximum distance of 2 edges of the WordNet graph. In particular we consider only the graph made by hypernym and hyponym relations for the nouns and only by the hypernym relations for the verbs. Then, in order to compute the distance between two input words we just use the Jaccard Index on the obtained sets.
- *Strategy 3 (S3)* based on the *average polarity similarity*, that takes into account if two adjectives belong to the same polarity region, i.e. positive, negative or objective. To compute this measure, we use the SentiWordNet resource [3]. In more detail using the knowledge of our resource, we divide the polarity region in three equal subspaces: positive, negative and objective. Given an adjective, we retrieve all its synsets from the SentiWordNet resource. Then, we classify each retrieved synset with a *local polarity indicator* based on the thresholds used in the subspaces definition. Then, we define a *global polarity indicator* for this adjective as the most common local polarity indicator among all of its synsets and we also associate to it a *global polarity measure* computed as the average values among the ones that belong to the same space of the global polarity indicator. Now, we compute the average polarity similarity between two adjectives as the minimum global polarity measure between the two words if both the adjective has the same global polarity indicator otherwise it is 0.

In Table 2, we depicted the strategy used to compute the distances among words according to their PoS label. We use the enumeration introduced in this section to represent the selected approach, 0 means that we choose to not compute any distances. We note also that in the case of adjective that are collapsed with their negation we apply the strategy 3 if also the other adjective was in the same situation. Now, for example let us consider two gram elements $g_1, g_2 \in \mathcal{E}^3$. The similarity $\text{sim}(g_1, g_2)$ is computed following the strategies defined in Table 2 for each couple of words obtained from words in g_1 and in g_2 , then the average value is returned. In particular, we note that just for gram elements belonging to \mathcal{E}^2 and \mathcal{E}^3 we consider all the possible couples. We note that also this approach can take advantage of some caching operation on all the resources involved.

	Noun	P. Noun	Adjective	Verb	Adverb
Noun	S2	0	0	0	0
P. Noun	0	S1	0	0	0
Adjective	0	0	S3	0	0
Verb	0	0	0	S2	0
Adverb	0	0	0	0	S1

Table 2: Strategies used to compute the distances among words based on PoS tagging. The enumeration is the one described in Section 6. P.Noun means Proper Noun

7. MINING THE COGNITIVE FEATURES

In this section we describe how we process a set of resources in order to detect the introduced Cultural Models. Let us suppose that we have a network of resources such as web pages. Each resource can be automatically processed in order to extract useful information such as images, tables, text content, links, html structures. Let us explain how we process the text data. We design a process flow, which is depicted in Figure 4, that is based on four main modules: *Resource Knowledge Processing*, *Cultural Knowledge Processing*, *Context Selection* and *Cultural Model Detection*. The Resource Knowledge Processing module has the aim to extract all the Text Signals from an input resource, as described in Section 4. For example, it takes as input resource a document d and it returns a structure made by a sentence s_i belonging to d and some useful Text Signals extracted from s_i such as $\langle s_i, \mathcal{E}_{s_i}, \mathcal{E}_{s_i}^2, \mathcal{E}_{s_i}^3, S_{s_i}^2, S_{s_i}^3 \rangle$. The Cultural Knowledge Processing module has the aim to derive the Cognitive Annotations related to a selected Cultural Model. It takes in input a Cultural Model $\mathcal{M} = \{e_1, \dots, e_n\}$ and for each $e_i \in \mathcal{M}$ it retrieves a Cognitive Annotation. It chooses for each e_i the most important Cognitive Annotation using the reliable measures computed in the processing described above. It returns for each $e_i \in \mathcal{M}$ a structure such as $\langle e_i, \mathcal{E}_{e_i}, \mathcal{E}_{e_i}^2, \mathcal{E}_{e_i}^3, S_{e_i}^2, S_{e_i}^3 \rangle$ where the sets are the union of the sets of gram elements of the same gram element type belonging to the same Cognitive Annotation. For example $\mathcal{E}_{e_i}^3$ is the union of all the tri-grams that belong to the Entity Text Cognitive Annotation selected to be representative for e_i . The *Context Selection* Module has the aim to choose some group of sentences that are indicative of our further analysis. The *Cultural Model Detection*, instead, has the aim to evaluate the presence of each Cognitive Feature in the initial resource. In this way we are able to understand if the considered Text Signals have the cognitive signatures related to the selected Cultural Model. Let us give more details about the last two modules in the following subsections.

7.1 Context Selection Module

In this module, we start to consider a different granularity for our analysis, in particular we define the *Context* as set of subsequent sentences. At this stage the initial resource, for example a document, can be seen as $\mathcal{C} = \{c_1, \dots, c_m\}$, being its generic element $c_i = \{ \langle s_{i-k}, \mathcal{E}_{s_{i-k}}, \mathcal{E}_{s_{i-k}}^2, \mathcal{E}_{s_{i-k}}^3, S_{s_{i-k}}^2, S_{s_{i-k}}^3 \rangle, \dots, \langle s_{i+k}, \mathcal{E}_{s_{i+k}}, \mathcal{E}_{s_{i+k}}^2, \mathcal{E}_{s_{i+k}}^3, S_{s_{i+k}}^2, S_{s_{i+k}}^3 \rangle \}$ a Context of $2k+1$ subsequent sentences, with $k < i$ together with all the text signals extracted for each sentence. In this module we define a filter able to select only the Context that we need to process by a next module. The filter is designed as a statistical decision process based on the analysis of the uni-gram of each Context. In particular we model the relevance of the Context in terms of trials of a binary random

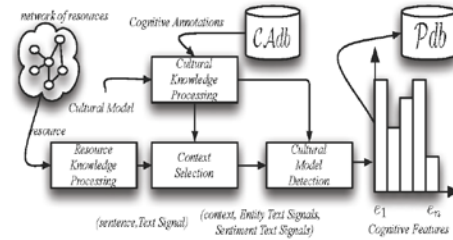


Figure 4: The modules used in our process.

variable (r.v). In fact, we map each uni-gram belonging to a context c_i to an independent and identically distributed (i.i.d) binary r.v and we define a kind of *relevance* of the input Context through a Bernoulli process. Let us consider the set \mathcal{E}_{c_i} made by the union of the different \mathcal{E}_{s_i} being s_i a sentence belonging to c_i and N_{c_i} its cardinality. We define a grade of relevance r as r success in N_{c_i} trial as follows:

$$P(r|N_{c_i}, \theta) = \binom{N_{c_i}}{r} \theta^r (1-\theta)^{(N_{c_i}-r)} \quad (3)$$

For our decision problem, we are interested in the Bayesian estimation of θ . This operation is done using as "observed trials" the N_{c_i} words. Let us now explain how we map the gram elements in a set of binary variables. We transform each uni-gram $g \in \mathcal{E}_{c_i}$ in a sequence of relevance (ro) or not relevance (nro) observation through the function f_r defined as follows:

$$f_r(g, \mathcal{M}) = \begin{cases} ro & \text{if } g \in \mathcal{E}_{\mathcal{M}} \\ ro & \text{if } \exists g^* \in \mathcal{E}_{\mathcal{M}} : dist(g, g^*) < \epsilon \\ nro & \text{otherwise.} \end{cases} \quad (4)$$

Being $\mathcal{E}_{\mathcal{M}}$ the union of all the uni-gram attached to the $c_i \in \mathcal{M}$, with \mathcal{M} the chosen Cultural Model, $dist$ a distance between two uni-grams computed according to the strategy defined in Section 6 and ϵ a fixed threshold. We use for the estimation of θ as prior a non-informative beta distribution $Beta(\theta|\alpha, \beta)$, with $\alpha = \beta = 0.5$. According to the Bayesian Analysis, the estimator $\hat{\theta}$ has a distribution $Beta(\alpha+n^{ro}, \beta+n^{nro})$, being n^{ro} and n^{nro} the number of times we observe a relevance or a not-relevance sample respectively. Now the selection process is computed as follows: i) we first select those contexts for which the base condition $E[\hat{\theta}] \geq 0.5$ is verified; ii) then we send to the next module those contexts whose discriminative measure of relevance (dr) exceeds a given thresholds. The dr is defined as follows:

$$dr = \frac{E[\hat{\theta}] - 0.5}{\sigma(\hat{\theta})} \quad (5)$$

being $\sigma(\hat{\theta})$ the standard deviation of $\hat{\theta}$.

7.2 Cultural Model Detection Module

In this module, we propose a model able to evaluate the diffusion of the Cognitive Features on the input resources by analysing the extracted Text Signals in order to extract cultural evidence from them. First, we traduce all the selected

Contexts in the previous module as binary strings using the Cognitive Annotations extracted from the selected Cultural Model. This process is made by a function f defined as follows:

$$f(\mathcal{A}_{c_i}^*, \mathcal{A}_{c_j}^*) = \begin{cases} 1 & \text{if } \mathcal{A}_{c_i}^* \cap \mathcal{A}_{c_j}^* \neq \emptyset \\ 1 & \text{if } \exists g_{c_j}^* \in \mathcal{A}_{c_j}^*, g^* \in \mathcal{A}_{c_i}^* : \text{dist}(g_{c_i}^*, g_{c_j}^*) < \epsilon_{c_i}^*, \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

Being $\mathcal{A}_{c_j}^*$ a set of text signal extracted from the sentences belonging to a c_j that was selected in the previous module and $\mathcal{A}_{c_i}^*$ the set of gram belonging to the selected Cognitive Annotation. For example $\mathcal{A}_{c_j}^*$ can be $\mathcal{A}_{c_j}^{S^3} = S_{s_1}^3 \cup \dots \cup S_{s_{n_{c_j}}}^3$, where $\{s_1, \dots, s_{n_{c_j}}\}$ are the sentences belonging to c_j . We note that in this phase we only considered the bi-grams and tri-grams. Then, we have dist and $\epsilon_{c_i}^*$ that are distances computed as describe in Section 6 and a fixed threshold related to the text element type and Cognitive Feature, respectively. We note that this distance requires that the input grams are of the same gram element type. This means, for example, that we compare a tri-gram extracted from an Entity Text Cognitive Annotation with a tri-gram coming from the Text Entity Signal of a Context. For sake of clarity, we depicted in Figure 5 how we generate these binary signals from a generic Context c_i . To evaluate how the Cognitive Features are spread around the Contexts, we considered a hierarchical bayesian model that can be seen as the generative models of these binary strings.

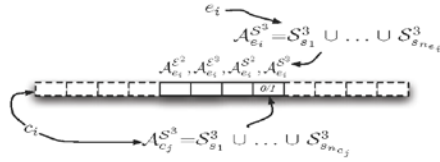


Figure 5: How we build the binary strings from the Context c_i using the approach described in Section 7.2.

These generative models are well studied in statistical natural language processing to inference topic distributions on corpus. Our approach has some similarity with the graphical model proposed in [6]. The model is depicted in Figure 6 using the Plate notation [6]. In particular in this generative model, as described in Figure 6, we have a document d described by a set of Context \mathcal{C} . From d we sample with uniform distribution a Context x . Then for each Context x , we sample a Cognitive Feature z from its set \mathcal{CE} with a multinomial distribution with parameters Θ . Then, from each Cognitive Feature z we sample a binary variable w from a binomial distribution with parameter ϕ four times. In this setting we have a learning problem, where we use the Bayesian theory. This means that we want to estimate the distribution of latent variables using some data and prior over these latent variables. In particular we use as prior the Dirichlet distribution α for the multinomial distribution and the Beta distribution (β) for the Binomial distribution. As data to observe we use the binary strings obtained from

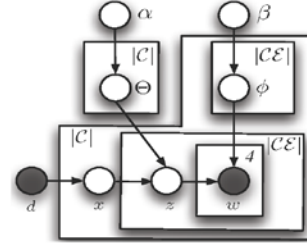


Figure 6: Hierarchical Bayesian Model used to estimate the distribution of Cognitive Features in a document d . The latent variables are represented by white nodes.

the different Contexts coming from a document d , that were selected by the previous module. We are interested to estimate the distribution Θ that gives the information of how the Cultural Features are spread around the Context. To estimate this distribution we use some equations used in the well known Collapsed Gibbs inference algorithms [6], that is typically used to estimate the latent variables in Bayesian graphical model. We note that we use this approach to measure a distribution of r.v.s rather than to classify new data by training a bayesian learner.

8. CASE STUDY

We apply our framework in the domain of the Islam religion, with the aim to understand how the beliefs introduced in Table 1 are spread around three main population: Moderate Arab, Moderate USA, Extreme. The data was collected from web sites in Arabic and English language, in particular they are collected using Google search engine both in English and in Arabic with some keywords related to our beliefs. In particular, we collected 80 documents, 23 of them were used to select some Cognitive Annotation for each belief defined in Table 1 and the others to run our experiments. The domain experts report for each belief a set of sentences that are used as Cognitive Annotations. We note that the Cultural Model considered in our case study is made only of Cognitive Features such as $\langle B, -, \delta \rangle$ or $\langle B, v, \delta \rangle$. In other words, we consider as a Cognitive Feature a belief with its values $\langle \langle B, v, \delta \rangle \rangle$ for the Context Selection module and the belief without its values $\langle \langle B, -, \delta \rangle \rangle$ for the Cultural Model Detection. We do not take into account an initial measure of the attitude of each belief so we start our process with $\delta = 0$. We compute also for each element in the Cognitive Annotation a reliable measure, which is a value in the interval of $[0, 1] \cap \mathbb{R}$ as described in Section 5. We select as Context a fixed group of 5 sentences, and we choose the following thresholds $\epsilon=0.8$ and $dr>0.8$ for the Context Selection module. For the Cultural Model Detection module, we use 0.8 for each $\epsilon_{c_i}^*$. We note also that for the document written in the Arabic language, we first run some machine translation procedure and then these documents were corrected by a native arabic speaker in order to overcome the problem related to the imperfection of the machine translation algorithms. In Table 3 is depicted the data about the dimensions of our collection and the average numbers of se-

	Num. of Documents	AVG Num. of Contexts	AVG Num. of selected Contexts
Moderate USA	24	866	43
Moderate Arab	18	623	66
Extreme	15	739	36

Table 3: Summary of the collected data

	AC-KM	R-KM	AC-KC	R-KC
Moderate USA	22	0.4	32	0.4
Moderate Arab	16	0.7	40	0.6
Extreme	22	0.8	12	0.6

	AC-CH	R-CH	AC-CD	R-CD
Moderate USA	9	0.7	34	0.7
Moderate Arab	14	0.7	48	0.8
Extreme	31	0.8	12	0.7

	AC-IES	R-IES	AC-IEI	R-IEI
Moderate USA	16	0.7	23	0.5
Moderate Arab	13	0.7	27	0.4
Extreme	22	0.6	17	0.4

	AC-JA	R-JA	AC-JI	R-JI
Moderate USA	19	0.5	33	0.7
Moderate Arab	22	0.8	42	0.6
Extreme	25	0.8	15	0.6

Table 4: Summary of the results in our case study. The full names of * in AC/R-{*} are depicted in Table 1.

lected contexts after running the Context Selection process. The results of this case study are described in Tables 4 and in Figure 7. In Table 4, there are represented the average number of contexts (AC-{*}) and the average value of the reliable measure (R-{*}) that is assigned to each Cognitive Feature. Each row in Table 4 is related to a member of the considered population. Eventually, in Figure 7, we have the average values of context assigned to each belief in log scale. As time performance, we note that for an average number of 700 contexts, 8 Cognitive Features, and 2000 iteration of Gibbs sampler, we obtained an estimation of Cognitive Features distribution in about 3 hours of wall-clock time on standard 3GHz 4GB RAM PC workstation. We note that Cognitive Features such as Coherence Homogeny and Diversity are good indicators of the cultural differences among our population, this is also justified by the better annotation that the domain experts did for those beliefs as suggested by the average values of the reliable measures associated to them.

9. CONCLUSION

In this paper we have presented a general framework to analyse cultural behaviour on text data. In particular we propose a methodology based on concepts such as Cognitive Features, Text Signals and Cognitive Annotations. We also proposed some computational methods in order to use our framework with some text data. These computational methods come from the area of Bayesian Learning. In particular we designed a graph model used to estimate the diffusion of cultural beliefs within a population. A Case Study in the extreme religious domain was also reported with some results. In this Case Study, we can see how the Cognitive Features can be used to discriminate among different population from a cultural perspective.

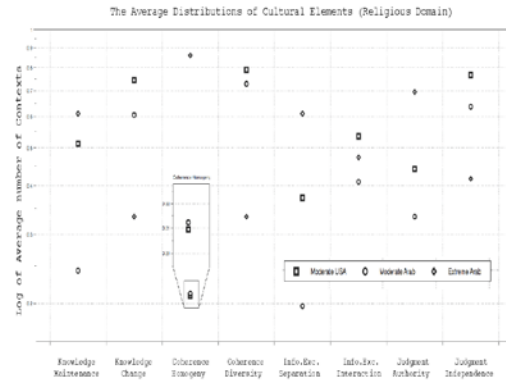


Figure 7: How the Cognitive Features (CFs) are spread over the different populations in this case study. In particular, we have on x-axis the CFs and on y-axis the log of average number of Contexts.

9.1 Acknowledgments

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APPENDIX C. SBP 2011 RESEARCH PAPER

This contains a research paper, which was presented at the International Conference on Social Computing, Behavioral-Cultural Modeling, & Prediction (SBP 2011).

Smart, P. R., Sieck, W. R., & Shadbolt, N. R. (2011) Using Web-Based Knowledge Extraction Techniques to Support Cultural Modeling. International Conference on Social Computing, Behavioral-Cultural Modeling, and Prediction (SBP'11), Maryland, USA.

Development of a Web-Based Knowledge Extraction System to Support Cultural Modeling

Paul R. Smart¹, Winston R. Sieck² and Nigel R. Shadbolt¹

¹ School of Electronics and Computer Science, University of Southampton, Southampton,
SO17 1BJ, UK

{ps02v, nrs}@ecs.soton.ac.uk

² Applied Research Associates, Inc., 1750 Commerce Center Blvd, N., Fairborn, OH, 45324
wsieck@ara.com

Abstract. The World Wide Web is a potentially valuable source of information about the cognitive characteristics of cultural groups. However, attempts to use the Web in the context of cultural modeling activities are hampered by the large-scale nature of the Web and the current dominance of natural language formats. In this paper, we outline an approach to support the exploitation of the Web to support cultural modeling. The approach begins with the development of qualitative cultural models (which describe the beliefs, concepts and values of cultural groups), and these models are subsequently used to develop an ontology-based information extraction capability. Our approach represents an attempt to combine conventional approaches to information extraction with epidemiological perspectives of culture and network-based approaches to cultural analysis. The approach can be used, we suggest, to support the development of models providing a better understanding of the cognitive characteristics of particular cultural groups.

Keywords: cultural network analysis, cultural ontology, cultural model, ontology-based information extraction, culture, cognition, knowledge extraction, world wide web

1 Introduction

The World Wide Web (WWW) is a valuable source of culture-relevant information, and it is therefore an important resource for those interested in developing cultural models. The exploitation of the WWW in the context of cultural modeling is, however, hampered both by the large-scale nature of the Web (which makes relevant information difficult to locate) and the current dominance of natural language formats (which complicates the use of automated approaches to information processing). In this paper, we describe an approach to support the use of the Web in cultural modeling activities. The approach is based on the development of ontology-based information extraction capabilities, and it combines the use of Semantic Web technologies and natural language processing (NLP) techniques with an epidemiological perspective of culture [1] and the use of belief networks to analyze culture [2]. Technological support for the approach is currently being developed in the

context of the IEXTREME¹ project, which is funded by the U.S. Office of Naval Research. In particular, we are currently developing a Web-based knowledge extraction system that incorporates a variety of information extraction, NLP and Semantic Web technologies. Such a system may be seen as an important element of an iterative approach to cultural modeling: one in which an initial (qualitative) characterization of the psycho-cognitive characteristics of a cultural group drives the acquisition of information that subsequently enables cultural analysts to refine, validate and extend the models developed at previous stages.

The structure of the paper is as follows. In Section 2 we outline what is meant by the term 'culture', and we describe an approach to cultural modeling that is based on the development of models representing the ideas associated with particular cultural groups. In Section 3 we describe our approach to the development of Web-based knowledge extraction capabilities to support cultural model development. This approach combines conventional approaches to information extraction with semantically-enriched representations of cultural models, and it seeks to provide a culture-oriented ontology-based information extraction (OBIE) capability for the WWW. Finally, Section 4 presents some conclusions and directions for future work.

2 Cultural Models and Cultural Network Analysis

Before addressing the use of the Web to study culture, we first need to define what is meant by the term 'culture'. As is to be expected in any highly interdisciplinary field, there are a variety of conceptions of culture. Our conception is distinctly cognitive in nature, and it is based on an epidemiological perspective [1]. A fundamental assumption of this perspective is that shared developmental experiences lead to important similarities in the mental representations (such as values and causal knowledge) that are distributed among members of a population. Culturally widespread ideas ground the distribution of behavioral norms, discussions, interpretations, and affective reactions in a population, and researchers working within the epidemiological perspective thus seek to describe and explain the prevalence and spread of ideas within populations.

Working from this perspective, we previously developed a technique called cultural network analysis (CNA), which is a method for describing the 'ideas' that are shared by members of cultural groups and which guide the decision-making behavior of group members [2]. CNA discriminates between three kinds of ideas, namely, concepts, values, and causal beliefs. The cultural models resulting from CNA use belief network diagrams to show how the set of relevant ideas relate to one another (see Figure 1 for an example). In general, we can distinguish two types of cultural models: qualitative and quantitative cultural models [see 2]. Qualitative cultural models present the ideas associated with a particular group, whereas quantitative models add information about the prevalence of these ideas in the target population. In addition to seeing the approach described in this paper as a means to validate and refine qualitative cultural models, it is also possible to see the approach as enabling a

¹ See <http://www.ecs.soton.ac.uk/research/projects/746>.

cultural analyst to estimate the relative frequency of ideas in a target population and thus develop quantitative extensions of the qualitative cultural models (see Section 3.6).

3 Web-Based Knowledge Extraction for Cultural Model Development

In this section, we describe an approach to cultural model development that combines CNA with state-of-the-art approaches to knowledge representation and Web-based information extraction. The aim is to better enable cultural model developers to exploit the WWW as a source of culture-relevant information. The approach we describe is based on a decade of research into OBIE systems [see 3 for a review], and it combines conventional approaches to information extraction with an ontology that provides background knowledge about the kinds of entities and relationships that are deemed important in a cultural modeling context. The first step in the process is to develop an initial qualitative cultural model using a limited set of knowledge sources [see 2 for more details on this step]. The second step involves the development of a cultural ontology using the qualitative cultural model as a reference point. This ontology is represented using the Ontology Web Language (OWL), which has emerged as a de facto standard for formal knowledge representation on the WWW. The third step is to manually annotate sample texts using the cultural ontology in order to provide a training corpus for rule learning. Rule learning, in the current context, is mediated by the (LP)² algorithm, which is a supervised algorithm that has been used to develop a variety of adaptive information extraction and semantic annotation capabilities [4, 5]. Following the development of information extraction rules, the rules are then applied to Web resources in the fourth step in order to identify instances of the entities defined in the initial qualitative cultural model. Step five consists in the identification and extraction of causal relations. The extraction of causal relationships is a difficult challenge because techniques for information extraction tend to focus on the extraction of particular entities in a text, rather than the relationships between the entities. We attempt to extract causal relationships using an approach that combines the use of background knowledge in the form of a domain ontology with the general purpose lexical database, WordNet [6]. Finally, in step 6, the extracted cultural knowledge is integrated, stored, and used to estimate the relative frequencies of the various ideas presented in the initial qualitative cultural model. We briefly describe each of these steps in subsequent sections.

3.1 Step 1: Develop Qualitative Cultural Model

The technique used to develop qualitative cultural models has been described in previous work [2], and we will not reiterate the details of the technique here. Figure 1 illustrates a simplified qualitative cultural model that represents an extremist Sunni Muslim's beliefs about current socio-political relationships between Islam and the West. The set of ideas represented in Figure 1 were extracted from articles that

describe jihadist narratives, and they are presented here for illustrative purposes. The cultural model illustrates concepts shared by the group, as well as their common knowledge of the causal relationships between those concepts. This shared knowledge influences expectations about how socio-political relationships will unfold, and it provides a basis for the selection of particular actions and decision outcomes; for example, the decision to support jihad.

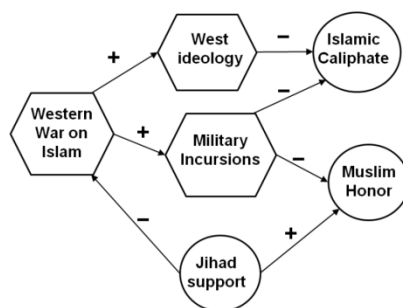


Figure 1. Sunni extremist cultural model of jihad (simplified).

Figure 1 shows the three different kinds of ideas that are the targets of a culture-oriented knowledge extraction system. These ideas include simple concepts such as “Western ideology” and “Muslim Honor”, each represented as closed shapes in Figure 1. It also includes causal beliefs; for example, the idea that Western ideology (e.g. secularism, nationalism) is inhibiting the formation of a unified Islamic caliphate and the idea that the West promotes this ideology because it is engaged in a covert war against Islam. These causal beliefs are represented as arrows in the figure, with the +/- symbols indicating the polarity of the causal relationship. Finally, Figure 1 portrays values using specific shapes, with circles indicating “positive” outcomes and hexagons indicating “negative” outcomes. Developing an Islamic caliphate is thus a good thing according to the cultural model. Maintaining (and enhancing) Muslim honor is likewise valued. According to the model, jihad is viewed positively and should be supported by the model’s adherents due to the perceived anticipated consequences for Muslims. Most directly, support for jihad decreases the chances that the West will continue its war against Islam, and it enhances collective Muslim honor.

3.2 Step 2: Develop Cultural Ontology

Once an initial qualitative cultural model has been developed, the next step in the process is develop an ontology that represents the contents of the model. The main reason this step is undertaken is that it enables the cultural model to be used to support information extraction. Over recent years, a rich literature has emerged concerning the use of ontologies in information extraction, and a number of important tools have been developed to support OBIE [3]. By converting the cultural model into

an ontology using standard knowledge representation languages, such as OWL, we are able to capitalize on the availability of these pre-existing tools and techniques, and we are also able to compare the success of our approach with other OBIE approaches.

The ontologies developed to represent the contents of cultural models are based around the notion of ideas as being divided into concepts, causal beliefs and values. These three types of ideas constitute the top-level constructs of the ontology, and subtypes of these constructs are created to represent the kinds of constructs that are represented in the cultural model. For example, if we consider the notion of 'Jihad support', as depicted in Figure 1, then we can see that this is a type of concept, and it is regarded as a positive thing, at least from the perspective of the target group. Within the ontology developed to support this cultural model we have the concept of 'support-for-jihad', which is represented as a type of 'jihad-related-action', which is in turn represented as a type of 'action', which is in turn represented as a type of 'concept'. Given the focus of the cultural model in representing causal beliefs, the notions of actions, events and the causally-significant linkages between these types of concept are often the most important elements of the cultural ontology.

3.3 Step 3: Develop OBIE Capability

In this step of the process, the aim is to create rules that automatically detect instances of the concepts, beliefs and values contained in the cultural model. There are clearly a number of ways in which this might be accomplished, especially once one considers the rich array of information extraction techniques and technologies that are currently available [7], and not all of these ways need to rely on the creation of symbolic rules (statistical approaches to information extraction have also demonstrated considerable success [see 7 for a recent review]). However, we prefer an approach that delivers symbolic extraction rules (i.e. rules that are defined over the linguistic features and lexical elements of the source texts) because the knowledge contained in the rules can be easily edited by subject matter experts. In addition, it is easier to provide explanation-based facilities for rule-based symbolic systems than it is for systems based on statistical techniques.

The approach to rule creation that we have adopted in the context of the IEXTREME project is based on the use of the (LP)² learning algorithm, which has been used to create a number of semantic annotation systems [4, 5]. The basic approach is to manually annotate a limited number of source texts using the cultural ontology that was created in the previous step. These annotated texts are then used as the training corpus for rule induction [see 8 for more details]. During rule induction, the (LP)² algorithm generalizes from an initial rule that is created from a user-defined example by using generic shallow knowledge about natural language. This knowledge is provided by a variety of NLP resources, such as a morphological analyzer, a part-of-speech (POS) tagger and a gazetteer. The rules that result from the learning process thus incorporate a variety of lexical and linguistic features. Previous research has suggested that rules could be defined over a large number of features. For example, Bontcheva et al [9] used a variety of NLP tools to generate 94 features over which information extraction rules could be defined. Of course, not all these features are likely to be of equal value in creating information extraction systems, and further

empirical studies are required to assess their relative value in the domain of cultural modeling (see Section 4).

3.4 Step 4: Extract Concepts

Once extraction rules have been created they can be applied to potential knowledge sources in order to detect occurrences of the various ideas expressed in the cultural model. Because most of the user-defined annotations will be based on the nodal elements of the cultural model networks, such as those seen in Figure 1, this step is particularly useful for detecting mentions of specific concepts in source texts. In the case of Sunni extremist cultural models this could, for example, include mentions of jihad-related concepts, for example '*Jihad is a means to expel the Western occupiers*', as well as references to aspects of Western ideology. In general, information extraction systems based on the machine learning technique described above (i.e. the (LP)² algorithm) have proved highly effective in identifying instances of the terms defined in an ontology, so we expect reasonable extraction performance for this step of the process.

3.5 Step 5: Extract Causal Relations

There have been a number of attempts to extract relational information in a Web-based context [see 7]. The use of ontologies in such systems plays an important role because they provide background knowledge about the possible semantic relationships that are likely to exist between the various entities identified in previous processing steps. Thus, if a system first subjects a text resource to entity-based semantic annotation, then it is able to use the ontology to form expectations about the kind of relationships that might be apparent in particular text fragments. When this background knowledge is combined with lexical and linguistic information, a relation extraction system is often able to identify relationships that would be impossible to detect based on a text-only analysis.

The approach to relation extraction that we have adopted in the case of the IEXTREME project is based on a technique that was previously developed to support information extraction in the domain of artists and artistic works [10]. The approach builds on the outcome of the previous step, which is concerned with the detection of concepts in the source texts. Importantly, once these concept annotations are in place, the relation extraction subsystem is provided with a much richer analytic substrate than would otherwise have been the case. In fact, it is only once such annotations are in place that the real value of the ontology (for the detection and extraction of relationships) can be appreciated; for the ontology provides background knowledge that drives the formation of expectations about the kinds of relationships that could appear between concepts, and once such expectations have been established, they can be supported or undermined by subsequent lexical analysis of the sentence in which the concepts appear.

Obviously, the nature of the natural language processing that is performed on the sentence is key to this relation-based annotation capability. It is not sufficient for a

system to simply form an expectation about the kind of relationships that might occur between identified entities in the text; the system also needs to ascertain whether the linguistic context of the sentence supports the assertion of a particular relationship. The decision concerning which relationship (if any) to assert in a particular sentential context is based on a strategy similar to that used in previous research [10]. Essentially, each relationship in the ontology is associated with a 'synset' (a set of synonyms) in the general-purpose lexical database WordNet [6]. When the relation extraction system executes, it attempts to match the words in a sentence against the WordNet-based linguistic grounding provided for each expected relationship. In addition to representing information about synonyms, the WordNet database also represents hypernymy (superordinate) and hyponymy (subordinate) relationships. These can be used to support the matching process by avoiding problems due to transliteration.

3.6 Step 6: Exploit Knowledge Extraction Capability

The knowledge extraction capability outlined in the previous steps provides support for the refinement, extension and validation of the knowledge contained in cultural models. The ability to detect instances of the ideas expressed in cultural models across a range of Web resources (including blogs, organizational websites, discussion threads and so on) provides a means by which new knowledge sources can be discovered and made available for a variety of further model development and refinement activities. The use of OBIE technology therefore provides a means by which the latent potential of the Web to serve as a source of culture-relevant knowledge and information can be exploited in the context of qualitative cultural modeling initiatives.

Aside from the development of better qualitative cultural models, the use of knowledge extraction techniques can also support the development of quantitative cultural models. As discussed above, quantitative cultural models extend qualitative cultural models by including information about the relative frequencies of particular ideas within the population to which the cultural model applies [2]. By harnessing the power of OBIE methods, the current approach provides a means by which ideas (most notably concepts and causal beliefs) can be detected across many hundreds, if not thousands, of Web resources. This provides an estimate of the prevalence of particular ideas in the target population of interest, and it provides a means by which the Web can be used to support the development of quantitative cultural models.

4 Conclusions and Future Work

This paper has described an approach to harnessing the latent potential of the Web to support cultural modeling efforts. The approach is based on the development of culture-oriented knowledge extraction capabilities and the use of techniques that support a cognitive characterization of specific cultural groups. Systems developed to support the approach may be seen as an important element of iterative cultural modeling efforts: ones in which an initial qualitative cultural model drives the

acquisition of information from a large number of heterogeneous Web-based resources. This, in turn, supports the effective refinement, extension and validation of cultural model content.

In terms of future work, a prototype system is currently being developed within the context of the IEXTREME project. This exemplifies the approach described herein, and it also enables us to address a number of research issues. One research issue concerns the need to adapt the information extraction techniques so as to optimize performance in the domain of cultural analysis. This includes the need to find the best mix of linguistic features with respect to the resources being analyzed [see 9]. A further issue for future work concerns the extension of the approach to support the detection and extraction of values. Values, recall, constitute one of three types of ideas associated with cultural models. The approach presented here, however, is clearly focused on the extraction of concepts and causal beliefs rather than values. Extending the approach to incorporate values may require us to consider techniques that have been developed to support opinion mining and sentiment analysis on the WWW [see 11 for a review].

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APPENDIX D. ACRONYMS

DOD	Department of Defense
CC	Coherence Consistency
CD	Coherence Diversity
CNA	Cultural Network Analysis
IE	information extraction
IEI	Information Exchange Interaction
IES	Information Exchange Separation
JA	Judgment Authority
JI	Judgment Independence
KC	Knowledge Change
KM	Knowledge Maintenance
LP2	Learning Patterns via Language Processing
OBIE	Ontology-Based Information Extraction
OVA	Ontology Viewer Application
OWL	Ontology Web Language/Web Ontology Language
PMIs	Polarizing Metacognitive Ideas
POS	Part of Speech
SBP	Social Computing, Behavioral-Cultural Modeling, and Prediction
W3C	World Wide Web Consortium